An approach for evaluating the impact of fulfillment operations performance

The case of a luxury fashion online marketplace

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Abstract

The ability to measure the expected return of initiatives, especially when facing multiple options, is indeed a valuable tool for establishing a prioritization of actions and financial efforts. In the context of luxury fashion - a market characterized by constant changes, there are certainly aspects that must be kept untouched, such as operational efficiency to deliver the promised good.

Farfetch is an online luxury fashion marketplace that operates all around the globe, due to its flexible model in which fulfillment operations are held by the partners it cooperates with. Albeit reducing the risk of carrying inventory, such a set-up reduces the visibility over the supply chain, since operations are essentially held by external entities.

Performance projects are dedicated to enhance Farfetch partners' operations, upon the belief that it may positively impact the organization. Therefore estimating the degree to which that impact can be translated into a financial measure is a matter of interest to select and prioritize projects based on their potential return.

This dissertation provides both a methodology and a formulation for estimating the ROI of performance projects. To achieve such goal, a holistic assessment of cost reductions from enhancing the quality of fulfillment operations is provided, by simultaneously focusing on the direct impact calculation as well as on understanding future implications of inappropriate fulfillment operations on customer retention and lifetime value - which is achieved by means of a survival analysis technique, particularly the Proportional Hazards Model.

The results are an attempt to quantify the cost of an imperfectly fulfilled order, whilst differentiating the cost per issue on a direct and indirect fashion, hence a cost matrix for operational issues is developed. Such approach allows for the estimation of what would be the beneficial outcome of reducing the level of operational issues on order fulfillment - the evaluated issues were those of lateness, incorrect items sent and stock unavailability. The final ROI model is developed based on this approach, and the prioritization rules were established according to a cash flow methodology.

Resumo

A avaliação do possível retorno de uma initiava, particularmente na existência de multiplas opções alternativas, é uma medida de que a organização pode benificar para o estabelecimento de regras de priorização e racionalização de esforços financeiros. No contexto da indústria da moda de luxo - caracterizada por constantes mudancas, existem certos aspetos a manter intactos, nomeadamente a garantia de eficiência e qualidade operacional, que permitem cumprir a promessa oferecida ao cliente final.

A Farfetch é um *online marketplace* de moda de luxo com a capacidade de operar em todas as partes do globo, principalemnte devido à cadeia de abastecimento flexível que até então tem vindo a estabelecer. As operações de gestão de inventário e cumprimento de encomendas são essencialmente da responsabilidade de entidades externas - como os parceiros com os quais coopera. Esta configuração, ainda que sustentável num ponto de vista de inventário, reduz significativamente a visibilidade sobre o estado operacional da cadeia como um todo.

Sobre a convicção da existência de uma relação direta entre uma melhor performance operacional e beneficios financeiros para a organização, os projetos de performance são iniciativas dedicadas à implementação de melhorias no fluxo operacional dos parceiros. Deste modo, é notoriamente pertinente estimar quantitavamente o nível de retorno esperado para a Farfetch, com a implementação de tais iniciativas.

Os fenómenos e metodologia descritos na presente dissertação, vieram a realizar-se com o principal objetivo de formular uma abordagem que permita estimar o Retorno de Investimento (ROI) de projetos de performance. Deste modo, avaliaram-se holisticamente as possíveis reduções de custos resultantes de uma redução de problemas operacionais - nomeadamente aqueles cuja responsabilidade é do parceiro. Adicionalmente, mostrou-se relevante a análise de implicações futuras de servir de forma inapropriada - no ponto de vista operacional, um cliente num dado momento. Para tal, conduziu-se uma análise de fiabilidade dos clientes Farfetch, por meio de um *Proportional Hazards Model*, de modo a associar os resultados ao *customer lifetime value*.

Os resultados obtidos são, de facto, uma abordagem à avaliação quantitativa de um problema operacional. Tal custo, com implicações a curto e longo prazo, foi calculado individualmente para as três métricas operacionais de interesse - atrasos, envio de produtos incorretos e ruturas de stock. Através desta abordagem, é possível estimar o potencial ROI resultante da redução do nível de ineficiência operacional e construir um modelo que, visando o estabelecimento de medidas de priorização, hierarquize a pertinência dos projetos por meio dos fluxos de caixa resultantes da aplicação de uma melhoria operacional transversal ao universo de parceiros.

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To all those who meant something at some point, I am thankful in my own mother tongue:

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"Tu és melhor – muito melhor!– Do que tu. Não digas nada."

Mário Cesariny

Contents

Acronyms and Symbols

AC	*Acquisition Cost*
AOV	*Average Order Value*
ATV	*Actual Transaction Value*
CAGR	*Compound Annual Growth Rate*
CLV	*Customer Lifetime Value*
CPRO	*Cost Per Retained Order*
EDD	*Estimated Delivery Date*
GMV	*Gross Merchandised Value*
LGD	*Loss Given Default*
OKR	*Objectives and Key Results*
PHM	*Proportional Hazard Model*
ROI	*Return on Investment*
RR	*Recovery Ratio*
SoS	*Speed of Sending*

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Chapter 1

Introduction

1.1 Luxury fashion online market

The way consumers engage in their purchases – i.e., their journeys from discovery, to sales channel selection and means of acquisition, has increasingly changed throughout time. Such phenomenon can also be observed in the context of luxury fashion, particularly regarding digital touch points. In fact, since tech-savvy generations accounted for 85% of the luxury market growth in 2017 and 47% of luxury consumers (Bain&Company, 2019), it should be expected a holistic shift in the industry. Focusing first on channels shift, online sales of personal luxury goods, which currently represent 8 % of such market, are expected to triple by 2025 (McKinsey&Company, 2016).

The underlying reason for 1 out of 5 luxury sales being held online (McKinsey&Company, 2016), should be explained by a myriad of transformations in the industry and consumers. On one hand, technology advancements enabled the remarkable growth of e-commerce and the establishment of omnichannel solutions for more effective distribution and response (McKinsey&Company, 2016). On the other hand, sources of inspiration for luxury goods are also shifting to an online nature, with nearly 80% of sales being influenced by several digital sources - especially social media (McKinsey&Company, 2016).

Even though defining what to deliver to consumers is a constant challenge, global luxury fashion players must understand the current industry transformation and redefine the way they deliver (Bain&Company, 2019) - by thinking digitally and agile to achieve faster market responses. For a better understanding of the aforementioned, accompanying the decline in physical shopping is the development of online strategies (McKinsey&Company, 2018). Figure 1.1 shows both the volume of sales and Compound Annual Growth Rate (CAGR), between 2014 and 2016, of different e-players in the luxury fashion market.

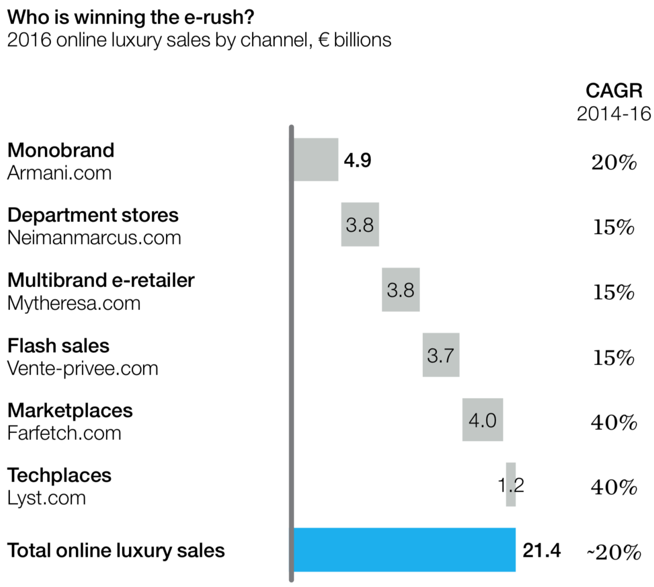

Figure 1.1: CAGR 2014-16: Breakdown by online luxury sales channel (McKinsey&Company, 2018)

Supported by the information provided in Figure 1.1, one may observe that luxury fashion consumers are looking for multibrand experiences (McKinsey&Company, 2016), therefore turning marketplaces like Farfetch an attractive option.

1.2 The Company

A plurality of definitions and classifications can be found for electronic marketplaces, as there is a constant adaptation to customer needs, business dimensions and service offerings (Wang, 2007). In spite of the breath of concepts, an electronic marketplace can be understood as a centralized market that brings multiple buyers and sellers together in a virtual sense (Grieger, 2003). Farfetch is an electronic marketplace for luxury fashion with the ability to operate and deliver goods all over the globe. It comprises a breath of product offering of over 2000 units, surpassing any of its direct competitors[1]. It is fundamental to understand that maintaining such an unique and extensive catalogue curation - that naturally accompanies the ever-changing fashion industry, is only possible due to the nature of the synergistic supply chain Farfetch was able to build. In fact, all of the available stock is not owned by Farfetch, yet by both the global brands and multibrand boutiques it cooperates with. This special operational set-up, even if sustainable in a stock ownership point of view, creates an equally particular order fulfillment process, held almost entirely by external entities. One understands this may generate limited visibility over the supply chain - especially on fulfillment processes, which makes it complicated to manage the touch points on customer experience that can be related to these areas of operation.

[1]Farfetch main competitors like Net-a-porter and Matchesfashion generally maintain a product availability within the range of 1000 to 1500 distinct units

As mentioned in the previous section, customers are seeking for a multibrand experience, which can certainly be provided by Farfetch. Plus, according to McKinsey&Company (2018), those who mitigate the risk of carrying inventory to sustain scalable growth will be in a healthier position in the luxury fashion e-commerce. Nonetheless, for the company to successfully and consistently offer the desired service level to provide a strong customer experience and further loyalty, there should be a focus on continuously improving its operations.

1.3 Project Motivation

Customer-oriented operations are a crucial practice to assure long-lasting customer satisfaction and collect valuable insights on quality management of internal processes. As to not further extend on the before-mentioned, a chapter within this dissertation will cover certain aspects of literature with respect to this topic.

Since Farfetch is not directly involved in the order fulfillment process - because the stock belongs to and is managed by its partners, controlling the level of operational efficiency is indeed a very demanding task. The motivation for the development of this dissertation derived then from two major pillars. One has to do with the current limitations on measuring the impact - positive or negative, of operational performance, on a monetary perspective. Secondly, from the strong belief that a better operational set-up generates greater satisfaction and commitment of customers, it is of great importance to infer on how much could the organization benefit, in terms of customer retention, from the improvement of its partners operational metrics.

This dissertation was developed within a department which provides external consultancy to partners [2], with the main goal of enhancing and strengthening their integration with Farfetch and overall operational efficiency. Consultancy projects can be those of initial on-boardings, creating better integration of information systems for both stock and order management, among others.

The consultancy projects explored throughout this dissertation are *performance projects*. These projects are included in the range of consultancy offerings of the Fulfillment Development department, and they focus on improving the operational flows of partners, transforming their activities into more efficient ones, hence allowing for allocation of higher capacity levels (scalability), without jeopardizing quality of service. Who primary benefits from these projects are indeed Farfetch's partners, although once speaking of a marketplace, operational metrics deviations are furthermore felt by the intermediary. Since these performance projects come with a cost i.e., dedicated time and physical presence of the team, estimating the potential Return on Investment (ROI) of such projects is of high interest. This dissertation provides an approach for the estimation of both the direct and long-term costs of operational performance deviations. These costs will be used to construct a ROI model based on prioritization rules - to understand on which partner(s) is more beneficial to invest on.

[2]Shall a partner be understood as the party who provides all the available stock displayed in the website, and is responsible for the processes between checking availability of stock until final packaging, within the order fulfillment process. With regard to the nature of the partner, they can either be a global brand like Prada, or a multibrand boutique.

1.4 Project Goals

As stated before, this dissertation focuses on understanding and evaluating the impact of Farfetch partners' operational performance on the business - considering ultimate implications on customer experience and satisfaction. *The main goal is then the establishment of a model that is able to provide insightful data for the prioritization of performance projects within the responsible department.* Prioritization rules will be established according to the current cost of operational deviations and the negative impact they might have on customer retention - which can be understood as long-term costs or negative after-effects on sales. To reach this goal, it is of uppermost importance a full acknowledgment of every point of contact between the partner and the company, as well as the identification of the stages during the order fulfillment process that are completely under the responsibility of the partner - since those are the ones to be improved. Additionally, it is necessary to evaluate current deviations from targeted operational metrics (cost evaluation) along with the assessment and quantification of long term effects based on historical transaction data.

1.5 Methodology

A model for prioritizing performance projects based on the level of ROI each one may generate, is to be developed and described through this dissertation. Notwithstanding the undeniable importance of relevant literature on the topic, the first action held on this project was to acquire the necessary knowledge on how the business operates - understand the "as-is" state, so that a differentiation of stakeholders could be established considering the level of involvement in operations. Information was gathered by casual interviews with relevant stakeholders and inductions during the beginning of the project. Hence, a connection between the business needs and relevant literature could be found to both investigate and support the forthcoming proposal. Following the above, a review on e-fulfillment operational performance measurements, operations impact on customer satisfaction, customer retention and finally customer lifetime value were necessary to identify which variables should be studied in the case. Afterwards, the direct costs generated by the partners' operational inefficiencies were calculated, as well as an understanding of the volume of "operational mistakes" undertook throughout two years of activity.

However, determining only the direct costs did not offer a proper evaluation of the real problem. In fact, the customer experience is impacted by operational inefficiencies, so understating to which level future purchases and engagement with the company is affected is of uppermost importance. Such approach was developed by modelling the retention rate of customers who suffered from such events, as to compare these with those whose orders were considered to be "perfect". Quantifying retention rate variations was done through evaluating the expected reduction of customer lifetime value.

Generically speaking, for the process of developing both approaches, it was necessary to extract all the necessary data - by means of structured query language (SQL), that was mainly constituted by sales, returns and refunds data. Extraction was followed by understanding and preparing the data for future mathematical modelling as well as for performing all the necessary calculations/ cost assessment.

1.6 Thesis Outline

The present dissertation is organized as follows:

- **Chapter 1** is an introductory section which provides a summarized description of the project, the goals and the followed methodology. Furthermore, a brief explanation of the company and its context are offered.

- **Chapter 2** highlights a selection of pertinent theoretical work, which was used to support the methodology undertook in the dissertation. Literature on the link between operations and customer satisfaction, customer lifetime value and semi-parametric survival analysis techniques are provided.

- **Chapter 3** provides a complete description of the problem to be addressed, as well as all the relevant components of which. The goal of this section is to facilitate the reader with a wholesome explanation of the project and its characteristics.

- **Chapter 4** presents the methodology followed to achieve the identified goal. The division of the chapter is into sections that address the particularities of each variable to be used in the final ROI model. Furthermore, it is provided an indication of how the model is constructed.

- **Chapter 5** is a final aggregation of the variables encountered in the previous chapter. Additionally, the final model capabilities are highlighted, as a result of the before-mentioned aggregation.

- **Chapter 6** is a contemplation of all the results and limitations found during the completion of the thesis. Finally, recommendations are made towards the identification of future work that could be done for further validating, enhancing and maintaining the results obtained.

Chapter 2

State of the Art

To better understand, address and describe the phenomenons given in the current problem, an initial coverage of relevant definitions and findings on literature is of uppermost importance. As stated in section 1.4, this dissertation is dedicated to the estimation of the Return on Investment Farfetch shall have from a performance project on a given partner. First, a coverage of Return on Investment definition and calculation is offered in this chapter, followed by an exposure of relevant topics to address the measurement of long term effects of a better operational set-up.

Measuring the long term effect of operational issues may be an intricate task. The thought process had to pass by understanding how can a long term impact on revenue be felt and quantified. In fact, who ultimately has the decision of purchasing a given item is the final customer, so accounting for his experience and satisfaction by means of analyzing historical transactions, can provide a set of important indicators to establish the desired connection.

The following sections of this chapter will also provide an overview of literature about customer satisfaction, loyalty and value. These topics selection derived from the need of understanding what drives customer behaviour on repurchase intents and ultimately retention, and how can the monetary value of a customer depend on the last. Additionally, for modelling customer retention, and understand how it can be affected by operational performance metrics, a coverage of a survival analysis model - namely the proportional hazard model, is provided.

2.1 Evaluation of investment decisions

As defined by Reilly and Brown (2011), " an investment is the current commitment of dollars for a period of time in order to derive future payments that will compensate the investor for (1) the time the funds are committed, (2) the expected rate of inflation during this time period, and (3) the uncertainty of the future payments.". Hence, estimating the degree to which future payments will cover the initial commitment represents an inestimable tool for decision making upon the time to invest. The investor's required rate of return is then utilized to measure the risk an investment may hold, as to weight all the possible investment outcomes and decide between several investment options (Reilly and Brown, 2011). When one invests, the main goal is to maximize profitability, therefore conducting a study prior to the investment should focus on evaluating the financial and economic feasibility an investment decision may hold (Lopes, 2012). Financial indicators such as performance ones, can be used in an initial stage of viability assessment. One of such indicators is the Return on Investment, however, profitability ratios alone prove to be insufficient to evaluate a certain investment project, as they do not comprise the value of money over time, and do not lay on cash flow analysis (Lopes, 2012). Consequently, other criteria should the calculated, such as the Internal Rate of Return (IRR) (to compare with the above mentioned Required Rate of Return), the Net Present Value (NPV) and Payback Period (PB).

2.1.1 Return on Investment (ROI)

The Return on Investment (ROI), as a profitability a ratio (and performance measure), establishes a relationship between the operating profit and the capital invested in the company (Lopes, 2012). For this reason, it gives a measure (commonly as a percentage) of the amount of return to be achieved from an investment, given its cost (Investopedia). Its gained popularity derived from the easiness of interpretation, and versatility of application to assess the potential of investment decisions. Plus, if calculated in the end of the project/investment (in a retrospective fashion), as it is based on accounting records, it provides objective outputs (Botchkarev et al., 2011). Notwithstanding its ease of use, it is important to note that for comparing investment decisions, one must assure the time horizon for the several options is comparable, as to not jeopardize the implications of the temporal value of money (Investopedia).

According to Mogollon and Raisinghani (2003), ROI is a fraction between the net gain earned as a result of the project, and the associated costs (what was spent to achieve a certain result). Hence, to estimate it, it is necessary to forecast both the initial costs, incremental ones, plus the expected benefits. Also from the same author, measuring ROI in the context of E-commerce applications can be adapted from the traditional formulation. One should determine the current cost (external and internal) of a certain process, alongside with the calculation of cost savings derived from the new process (benefits in productivity/efficiency should be included). Finally, the assessment of the investment/project cost should be also added (as a numerator). The final formula can then be provided on equation 2.1.

$$ROI = \frac{(CurrentProcessCost - NewProcessCost) + OtherBenefits}{CostsofImplementingtheProject} * 100 \tag{2.1}$$

As for evaluating ROI, one understands that the higher the ratio (positive), the greater the positive outcome, since surpassing the costs of the project/investment, means a ratio ideally higher than 1.

Additionally, it is valuable to mention that on a benefit perspective, there are oftentimes intangible positive outcomes that must be considered, even if their estimation/calculation can represent an arduous task. The ROI can include the valuable outcome these benefits arise. A compilation of tangible and intangible benefits to monitor in the context of E-business (and on the ROI calculation) is provided in Figure 2.1.

E-Business strategic plan achievements
- completion of steps of the E-business project plan

Business value of E-business initiatives
- profitability of the web site
- Return on Investment (ROI) or Information Economics
- direct online contribution to revenue
- operational cost reductions
- cost reductions of acquiring a new customer
- cost reductions of customer relationship management
- cost reductions of promotional material

Compliance with budget
- actual versus budgeted expenses (ongoing development and maintenance)

Figure 2.1: Measures for Business Contribution (Van Grembergen, 2004)

In conclusion, Mogollon and Raisinghani (2003) and Schlegel (2001), have listed (among others) intangible output benefits that can be associated to the customer side:

- Increased customer satisfaction and retention;
- increased customer base;
- reduced customer support requirements;
- reduced fulfillment and customer response errors.

In the context of this dissertation, a special focus on intangible benefits related to the final customer is to be provided and evaluated in the following sections.

2.2 Operations impact on customer loyalty

A great attention has been given towards defining customer loyalty, through its determinants and implications in the long term success of the business, especially in the context of service companies (Kumar et al., 2011). This reality rises from the fact that customer acquisition, besides being a difficult task (in terms of time and effort), requires also an investment higher than that of retaining existing ones (Ennew, 2003). Hence, on a financial point of view, customer loyalty proofs its interest since it is positively correlated to profitability and increased market-share, according to Anderson et al. (1994). In fact, the adjacent factors of customer loyalty in a given organization are those to be defined internally, however one can identify relevant precedents on the construction of loyalty. Such prior instances can be customer satisfaction, trusting beliefs and perceived value (Lin and Wang (2006) and Sirdeshmukh et al. (2002)). According to Kumar et al. (2011) the main drivers of customer loyalty are those to be observed in Figure 2.2.

As stated before, increased customer loyalty may induce increased profitability. Notwithstanding other factors, customer satisfaction is a strong predictor of repurchase intentions, which in turn represents a main driver of loyalty (Anderson et al., 1994).

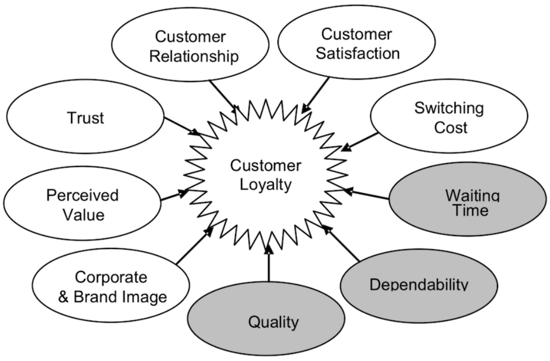

Figure 2.2: Main drivers of customer loyalty (Kumar et al., 2011)

What drives customer satisfaction? Among several factors, one may find that there is a strong relationship between customer satisfaction and operations performance, once enhanced quality (relative to operational elements) corresponds to positive behavioural intentions (Zeithaml et al., 1996). Service performance can be divided into two segments. The marketing-oriented dimension (Collier, 1991), the one that dues respect to relational elements, i.e., activities developed by the firm to understand the needs and expectations of customers, as to design relevant solutions and processes. The second is the operations-oriented dimension of service quality, with elements that are consistent quality, productivity and efficiency (Stank et al., 1999). Indeed, operational elements related to product availability and condition as well as delivery reliability and speed were found to influence customer satisfaction and repurchase intentions in a good manner (Stank et al., 1999). Plus, it was found that among several factors that may help defining service quality, performing with the promised service, dependably and accurately, was found to be the most preponderant one (Berry, 1995).

Also found by Kumar et al. (2011), the underlying hypotheses tested in the study, namely:

- The processes of service quality, that due respect to operations performance, such as: quality, dependability and speed, do not perform in an isolated manner;
- increased demand, if operations performance is negatively affected, there will be a negative impact on customer loyalty.

Were found to be proven. The conclusions on the first hypothesis proved that under higher dependability, the other elements were negatively affected. As for the latter, if quality falls (in terms of given promise) with increased volumes, then loyalty will follow the same pattern. In conclusion, it is relevant to note that post-purchase operational performance is that one which heavily affects loyalty. Hence, it is more important to meet the expectations of a given promise, than to focus on customer acquisition with such a promise.

Disappointment theory - which is rooted in the field of behavioral decision theory (Bell, 1985), highlighted in a study by (Homburg et al., 2005), suggests that disappointment occurs when the outcome of a choice is below prior expectations. However, when the outcome positively excels such expectation, elation arises. In fact, as validated by (Homburg et al., 2005) , there is indeed a positive relationship between customer satisfaction and willingness to pay (WTP). Observe Figure 2.3 to understand the functional structure of such relationship:

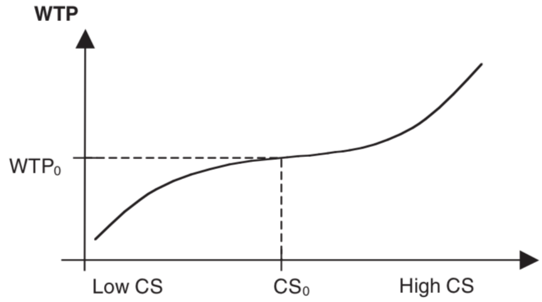

Figure 2.3: Inverse S-Shaped Function for the relationship between Customer Satisfaction and WTP - Hypothesized on the Basis of Disappointment Theory (Homburg et al., 2005)

Furthermore, beyond WTP, it is also observable a positive relationship between repurchase behaviour and customer satisfaction on Figure 2.4:

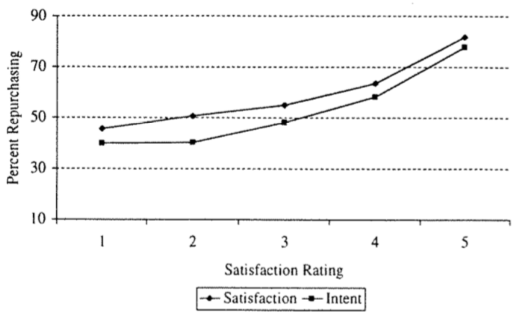

Figure 2.4: Repurchase Behaviour and Customer Satisfaction (Mittal and Kamakura, 2001)

Bottom line, several studies have demonstrated that customer satisfaction is a key driver of customer loyalty (Mittal and Kamakura, 2001), and that loyalty has a powerful impact on firms' performance - measured by increased revenue, reduced customer acquisition costs, and lower costs of serving repeat purchasers which lead to greater profitability (Lam et al., 2004). Consequently, it is of great interest for the firm to guarantee a level of service that allows for meeting - or positively exceeding, the customers' expectations. To conclude and further understand the above-mentioned impact on profitability, refer to Figure 2.5 to observe the relationship between customer retention and firm profitability:

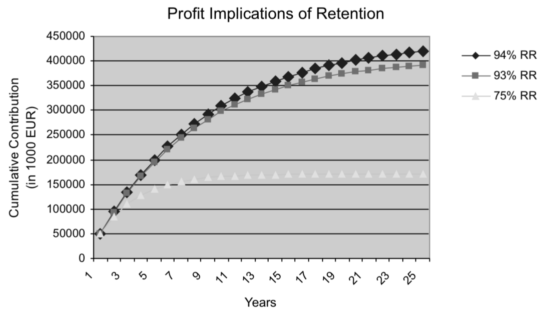

Figure 2.5: Real-life example of retention rate (RR) implications on profit (Van den Poel and Lariviere, 2004)

2.3 Customer Lifetime Value

Customer Lifetime Value (CLV) can be defined as the present value of all future profits of a customer (Khajvand et al., 2011), throughout the entire lifetime with the company, which for most applications is calculated for a time-frame of three years (Kim et al., 2006), allowing for the coverage of most life-cycles - i.e., product and customer. Measuring CLV and being able to interpret it for its various applications, especially in the context of Marketing and Product/Customer Strategy, can be a powerful tool to prioritize actions and make consistent decisions (Kahreh et al., 2014). For example, since operating with limited budgets, increasing the return on marketing investments is a matter of concern. Hence, being aware that different customers (segments) are expected to have different values, may help on building a more sustainable strategy, by tailoring different types of marketing instruments (Borle et al., 2008) - since not all customers are equally profitable.

According to Gupta et al. (2004), the CLV of current and future customers, is a good proxy of the overall firm value (or its stock price). A conceptual framework proposed by Gupta et al. (2006), to estimate such value, can be observed on Figure 2.6:

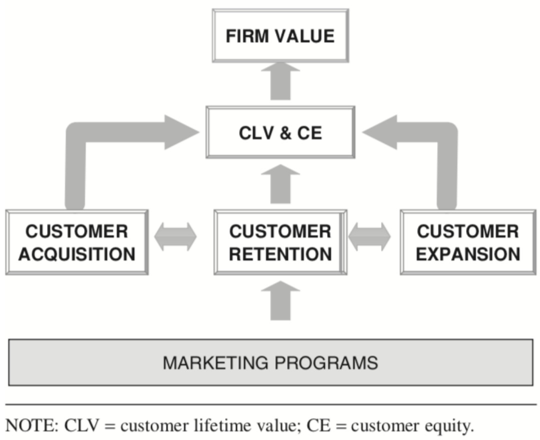

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Figure 2.6: Conceptual framework for modelling CLV (Gupta et al., 2006)

2.3.1 Calculating Customer Lifetime Value

Several methodologies can be used to estimate CLV, however it is most likely to be advantageous to use those which incorporate past customer behaviour, to estimate the future behaviour and consequently predict the remaining CLV (Schmittlein and Peterson, 1994). These methods can be, for example, the negative binomial distribution (NBD) – Pareto model applied by (Borle et al., 2008), hazard models of customer retention (Gupta et al., 2006), and the Bayesian approach proposed by (Rossi and Allenby, 2003).

Albeit having several modelling techniques to estimate CLV, the fundamentals of calculating it are indeed similar to the discounted cash flow approach. As suggested by Gupta and Lehmann (2003), equations 2.2 and 2.3, are the basic formulations for estimating CLV for a discrete and continuous (infinite) time horizon, respectively:

$$CLV_{DiscreteTime} = \sum_{t=0}^{T} \frac{(p_t - c_t)r_t}{(1+i)^t} - AC \tag{2.2}$$

$$CLV_{\infty} = \sum_{t=0}^{\infty} \frac{(p_t - c_t)r^t}{(1+i)^t} - AC = m\frac{r}{(1+i-r)} \tag{2.3}$$

where:
p_t is price paid by a customer on time t
c_t is the direct cost of servicing a customer at time t
r_t retention rate at time t ("being alive" at that time)
AC is the customer acquisition cost
i is the firm's cost of capital
T is the time horizon for the estimate
m is the margin of serving a customer

To conclude, it is additionally noted by Gupta et al. (2006), that most modeling approaches ignore competition because of the lack of competitive data, which would be a valuable input. Plus, selecting between the formulations for estimating and updating CLV, depends both on the required frequency and dynamics of the particular market.

2.4 Survival analysis

Survival analysis is a collection of statistical methods for which the outcome variable of interest is the time until an event occurs (for example, customer churn). Therefore, survival analysis focuses on the distribution of survival times (Mavri and Ioannou, 2008). It is indeed a matter of interest to estimate unconditional survival distributions, however most interesting survival modeling examines the relationship between survival and one or more predictors (the covariates) (Fox, 2002) -

i.e., establish descriptive or predictive models in which the risk of an event depends on covariates (Van den Poel and Lariviere, 2004).

Also noted by Mavri and Ioannou (2008), the characterization of the distribution of survival times may be achieved by means of three functions:

1. The survival function (S);

2. The probability density function (p.d.f.) - also known as the the unconditional failure rate (f);

3. The hazard function (h).

Being T the variable that randomly describes the survival time (the event time for some particular individual), one may formulate the before mentioned functions in the following manner:

$$S(t) = P(of being "alive" longer than t) = P(T > t) = 1 - F(t) \tag{2.4}$$

Where F(t) is the cumulative distribution function of T.

Then, t he probability density function f(t) can be formulated as follows:

$$f(t) = \lim_{\Delta t \to 0} \frac{P(of Ending the "Alive" Period On (t, t + \Delta t))}{\Delta t} \tag{2.5}$$

Or, similarly, f(t) can be written as, according to 2.6:

$$f(t) = \frac{dF(t)}{dt} = -\frac{dS(t)}{dt} \tag{2.6}$$

And finally, the hazard function can be written as:

$$h(t) = \lim_{\Delta t \to 0} \frac{Pr(t \leq T < t + \Delta t / T \geq t)}{\Delta t} \tag{2.7}$$

Or, with respect to f(t) and S(t):

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} \tag{2.8}$$

2.4.1 Proportional Hazards Model

A model that allows for performing a survival-times analysis while studying the relationship between survival and covariates (plus testing the statistical significance of that effect), is the Cox proportional-hazards regression model (Cox, 1972). Once being a semi-parametric model[1], hence the baseline hazard function can be left unspecified - which is a valuable aspect of this formulation, considering the morose task it is to find the distribution that describes the survival-time data.

The proportional hazards model is formulated as follows (Helsen and Schmittlein, 1993):

[1]According to Fox (2002), the Cox proportional-hazards regression model is semi-parametric, since the baseline hazard can be left unspecified, whereas the covariates enter the model in a linear fashion.

For an individual (being it a customer, a machine, etc.) having the covariates values $x_{1t}, x_{2t}, ..., x_{kt} \equiv x_t$, $h(t \mid x_t)$ denotes the hazard rate at time t, the hazard rate is given by equation:

$$h(t \mid x_t) = h_0(t)\phi(x_t, \beta) \tag{2.9}$$

where:

β_j indicates the effect of the covariate x_{jt} on the hazard rate, and can be viewed as the constant proportional effect of x_{jt} ;

$h_0 t$ is the baseline hazard function;

$\phi(x_t, \beta)$ adjusts $h_0 t$ up or down proportionately to reflect the effect of the measured covariates.

The estimation of the β vector is termed the proportional hazards regression and, in most applications, ϕ is formulated in such a manner that the hazard rate can be re-written as:

$$h(t \mid x_t = h_0(t)e^{\beta'(x_t)} \tag{2.10}$$

In terms of interpreting the coefficients of the predictor covariates, it may easier to follow the transformation of β_j as: exp (β_j), in which a value of exp (β_j) higher than 1 increases the hazard, whereas a value smaller than 1 decreases it.

Estimating the hazard model can be performed through determining the partial likelihood of the duration a certain individual (i) experienced - i.e., for an observed time t at which a duration is experienced, the partial likelihood that such duration has occurred can be written as:

$$L(i \mid t, j_1, ..., j_{n(t)}) = \frac{h_i t}{\sum_{k=1}^{n(t)} h_{jk}(t)} \tag{2.11}$$

Incorporating equation 2.10, the partial likelihood estimate is:

$$L(i \mid t, j_1, ..., j_{n(t)}) = \frac{e^{\beta'(x_{it})}}{\sum_{k=1}^{n(t)} e^{\beta'(x_{jkt})}} \tag{2.12}$$

To determine whether a fitted Cox regression model adequately describes the data to study, it should be studied whether there is a violation of the assumption of proportional hazards (Fox, 2002). Proportionality implies that the hazard for any individual is a fixed proportion of the hazard of any other individual (Boucher and Kerber, 2001). Furthermore, a problem that often arises in empirical studies, is the existence of highly correlated variables - that is multicollinearity, which makes the parameter estimates unreliable (Van den Poel and Lariviere, 2004). Another restriction of this model highlighted by the previous study, is the non-interaction between covariates and time, hence the group of time-varying covariates being an exception to this rule - meaning that the ratios of the hazard do not remain constant when incorporating time-varying covariates into the model. However, according to (Allison, 1995) this does not create a real problem for the likelihood estimations.

To conclude, the described technique allows to incorporate both discrete and continuous measurements of event times, as well as handle observations (or individuals) that did not experience the event (that is, censored observations) (Kumar and Westberg, 1997) - for some individuals the time to failure may be observed completely, whereas for others we only have partial observation until some specific censoring time. Therefore, it is important for a sample to be composed by as many censored cases as uncensored ones (Van den Poel and Lariviere, 2004). Especially in the context of customer survival analysis, a balanced sample enhances the reliability on discriminating between defectors and non-defectors (Yamaguchi, 1992).

2.4.2 Application on inter-purchase timing

In marketing applications it may be interesting to analyze the effect certain initiatives have on repeated purchase intent as well as purchase-timing decisions. Hence, the covariates for this type of applications may include chooser-specific (consumer characteristics), and choice-specif (brands, promotions, special display, etc.) ones (Kuo and Chen, 1999), that shall be allocated to each individual purchase of a particular subject. Highlighted by Seetharaman and Chintagunta (2003), understanding the dynamics of inter-purchase timing as well as the effects of covariates that increase or decrease such variable, may be interesting on (i) a managerial point of view, since one might use such data to decide on the timing between promotional actions and (ii) on stock management perspective, where knowledge of depletion rates might allow to cut back costs.

The formulation for inter-purchase time , as suggested by Seetharaman and Chintagunta (2003), is given by the set of equations presented bellow:

If combining equations (2.8) and (2.10), one can re-write the probability density function f(t) as:

$$f(t,X_t) = h(t) * e^{X_t\beta} * S(t,X_t) \tag{2.13}$$

Which is equivalent to:

$$\frac{dF(t,X_t)}{1-F(t,X_t} = h(t) * e^{X_t\beta} * dt \tag{2.14}$$

Knowing the lower limit of integration corresponds to the time of the individual's previous purchases, the first-order differential equation can be solved as:

$$\int_0^{F(t,X_t)} \frac{dF(u,X_u)}{1-F(u,X_u)} = \int_0^t h(u) * e^{X_u\beta} * du \tag{2.15}$$

Solving for the survival function S(t):

$$S(t,X_t) = e^{-\int_0^t h(u)*e^{X_u\beta} du} \tag{2.16}$$

Substituting the previous equation on equation 2.13, $f(t,X_t$ represents the probability density associated with the purchase event that occurs at time t and covariate vector X_t:

$$f(t,X_t) = h(t) * e^{X_t\beta} * e^{-\int_0^t h(u)*e^{X_u\beta} du} \tag{2.17}$$

To conclude, the likelihood function given bellow, can be maximized to estimate the parameters of the PHM at the individual level:

$$L = \prod_{j=1}^{n} f(t_j - t_{j-1}, X_j) \tag{2.18}$$

Where n represents the total number of purchases made by the individual, whereas t_j stands for the calendar time associated with purchase j.

Chapter 3

Problem Statement

As mentioned in the introductory section of the document, this dissertation holds the purpose to establish a comprehensive view over the cost of operational inefficiencies, as to formulate a model which aims to support performance projects allocation. Farfetch's business model is quite peculiar, in the sense that all the stock available on the website does not belong to the company. Yet it is owned by the several collaborating partners who are willing to sell their products on this online channel. Hence, stock management and *on-time* point of sales visualization of every partner is particularly challenging for the organization.

The partners operating in Farfetch are considerably different in several aspects. One partner can be a small boutique in Italy, or a global brand distributing goods all over the world, owning several stock and shipping points, that may or may not be fully integrated with Farfetch order management systems. Such distinctive characteristics are reflected in the way operations are established, since they are particular to each and every one. In terms of sales volumes and *online/offline* sales ratio, the dimensions are as well disparate. These contrasting features introduce considerable variability in the fulfillment process. Therefore, the homogenization of order processing in the particular context of a partner, is very important to reduce inconsistency and waste, which ultimately affect the end-customer experience with Farfetch.

As to tackle such ultimate consequences, the Fulfillment Development team hopes to address the particularity of a partner, by consulting them on how to achieve the best operational set-up. However, since these projects are a complimentary service, it is necessary for Farfetch to evaluate the true cost of a partner holding a poor operational performance. An accurate cost estimate is critical for deciding whether to take on a project, and for ensuring that projects remain financially feasible - as to avoid cost overruns.

3.1 E-fulfillment - the company context

An order is placed in the website, just like in any other online marketplace (like *Amazon* or *Alibaba*). A natural subsequent process should be that of creating an internal order list that ignites the fulfillment operations in a stock point. However, since Farfetch does not own stock, it is necessary for the selected partner to check availability. This step mirrors the first complexity of this marketplace, since the same product can be provided by several partners, and Farfetch is not certain that the selected partner still owns the product. Once availability is confirmed, the order processing starts at the partner side, and is constituted by several steps, that can be briefly consulted in Figure 3.1. A detailed view over the common operations held by partners is provided in the following subsection.

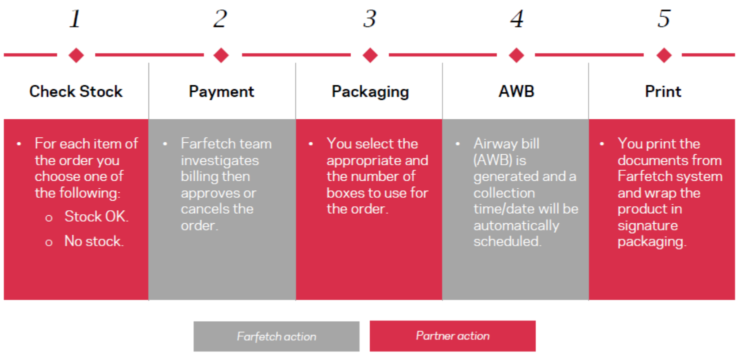

Figure 3.1: Order processing steps to be followed by both Farfetch and the partner *in* Farfetch Documentation

3.1.1 Partner operations

Even if considerably different from each other, there are several steps in the order fulfillment process that must be covered by the partner and reported to Farfetch. Those steps are listed below:

- **Check stock:** known internally as *Step 1*, this step is for assessing whether the ordered product is available in the stock point(s). In case it does, the upcoming processes occur right afterwards. If it does not exist anymore in the first selected partner, there is a second partner allocation for the same product. However, if the product was solely sold by the first, then a *No Stock* happens. The last trial run is what is called an *Item Swap*, in which a different product is suggested to the customer.

- **Decide Packaging:** since the majority of shipping costs are generally supported by Farfetch and charged by volumetric weight, it is important for the packaging to be as accurate as possible to avoid unnecessary extra costs. Plus, an unfitted packaging can jeopardize the *unboxing* experience of the final customer. Hence, packaging accuracy is an operational metric closely followed by Farfetch, and is also to be improved in the context of performance projects. This step is commonly known as *Step 3*.

- **Airway Bills - *Print Documents*:** after placing the item in the selected packaging, the partner must also indicate to Farfetch that the order is ready to be sent out; once being an intermediary, the company is responsible for providing all the necessary documents that must be attached to an order - i.e., the airway bills for both sending and returning the item, so that the correct information is passed to the courier and final customer. This process initiates what is internally known as *Step 5*.

- **Manifest Report:** A collection of proofs of delivery for all the orders being picked by the courier must be signed by both parties - the partner and the courier, as a formal indication that the orders left the stock point and initiated their time in transit. Whenever this step is finished, one reaches the end of *Step 5*.

3.1.2 Current evaluation metrics

As highlighted before, it is quite challenging to accurately and exhaustively monitor fulfillment and delivery operations, to guarantee a seamless customer experience, since those operations are not directly held by Farfetch. Hence, to evaluate the partner's operations - on the fulfillment side of order processing, there are certain metrics that are transversely over-viewed by the organization. Such metrics are then evaluated - on a partner level, comparatively to the internal targets, as to establish proper incentive services for either congratulate or penalize the partners' operational performance. An incentive service is, indeed, a practice to guarantee that a focus on operational excellence is transversely shared among the fulfillment stakeholders. Based on the operational performance of the previous month, a partner may receive back a percentage of their Actual Transaction Value (ATV) (the aggregate of Sales Prices for all orders less any Cancellations and Returns and Sales Taxes) if operating properly or, on the contrary, give back to Farfetch a certain percentage if under-performing. Appendix A provides a more detailed view on the design and calculation of incentive services.

The currently evaluated fulfillment operations metrics are:

1. **Speed of Sending:** This metric dues respect to the metric of speed. *Speed of Sending* retrieves the time between receiving an order and having it prepared to send - i.e., time for completing all the steps identified on section 3.1.1. Commonly identified as *SoS*, it can be given either as a gross time interval (that includes Weekends and any other day in which a particular partner does not function - given a national holiday, etc.), or a net time interval which excludes these days to give a right indication of the processing time. This metric is then followed as follows:

    - **Percentage of *SoS* (net) under one day:** As a new target for fulfillment operations, the percentage of orders allocated to a partner that were processed within one day are registered. The percentage should be ideally of 80%.
    - **Percentage of *SoS* (net) under two days:** As the initial yet most monitored target, SoS under two days can be taken as the service level agreement Farfetch comprises. Therefore, the great majority - namely 96.3% of orders should be processed - on the partner side, during this net time-frame.

    Speed of Sending is a very important metric also for the calculation of the Expected Delivery Date (EDD), because alongside the *Time in Transit*, it is used to provide the final customer with an expected Lead Time - or EDD. Hence, the greater the level of speed, the greater the maximization of time provided for delivery operations, given an EDD. Accuracy on this level, is of major relevance for managing customer expectations.

2. **No Stock:** Farfetch allows for the order to be placed given an internal indication of stock availability for the selected item. However, as indicated before, this level may or may not be updated. Hence existing the probability of stock unavailability on the partner level - *No Stock* events are given as a percentage of the number of orders allocated to a certain partner. This metric is the one associated with availability, and Farfetch sets the target of 1.30% (upper-bound).

3. **Wrong Items:** Due to the complexity of the marketplace and the variability of partners engaging with the organization, it is of a natural expectation that not all orders will be sent defect-less, to which accuracy dues respect. Consequently, quality of service also relies on order accuracy, and in the context of Farfetch, it is given (on an individual partner level) by the percentage of wrong item returned orders over the total amount of returns. The percentage threshold is calculated based on the number of returns, hence being dynamic per case.

In the context of this dissertation, only fulfillment operational issues are going to be covered, therefore lateness brought by delivery services is not going to be studied. This is due the fact that performance projects - the product for which ROI will be estimated, are only dedicated to enhance partners' fulfillment operations.

3.1.3 Measuring operational performance impact on the company

The evaluation of operational issues can be highly challenging given the levels to which it can extend - i.e., not only they represent immediate costs (essentially understood as those which purpose is for fixing the issue - corrective actions), but they may also have future implications on the organization, especially on the final customer side. Such cost implications - indirect costs, can be a decrease in customer satisfaction and consequently retention, poor *word of mouth* and a negative effect on switching costs given the competitiveness of the market, as to mention a few.

The current direct costs are being calculated on a financial point of view, aggregated to the whole block of operational costs. Although, these negative results should also be properly quantified and monitored by operations teams, since they are commonly associated as the cost centers of an organization. Plus, the level of impact per operational issue - on an indirect point of view, can be translated into a financial measure, that besides being easier to follow, provides a comparable level of magnitude of a certain issue, as to prioritize actions of operational improvement. It is to note that there are currently no indications/estimates of how much an operational issue represents - in terms of customer retention and ultimately customer lifetime value (financial perspective).

The direct impact can be divided in the following manner:

- **Compensation Costs (Refunds or *surprise* actions):** that may include Return Costs in case the compensation followed such event. These are mainly constituted by shipping, payment transactions, item (price match or full price refund) and extra compensation - i.e., used mainly with the intent of retaining the customer.
- **Contacts per Order:** the allocation of resources for customer and partner service, that is positively correlated to the level of operational performance issues.

The extent to which the partner covers these costs (excluding immediately Service Operations) can be given by the Recovery Ratio (RR) (or Loss Given Default (LGC), as it is 1-(RR)). Such metric is again calculated and followed by partner supporting teams. However, they will only provide financial aid if there is an explicit connection to their side of fulfillment operations. The context of this dissertation includes the calculation of these direct costs per operational issue that is associated with the partner's performance. Plus, an indication of the level of coverage (RR) per issue will also be provided. Finally, an estimation of financial losses resulting from not meeting the final customer's expectations - indirect costs / future impact on revenue, since it is expected to find reduced customer retention in the long run if fulfillment operational issues are part of previous purchasing experiences.

3.2 The Problem

As one of the most known and widely applied performance metric in business, being able to estimate the Return on Investment of a certain initiative, is a useful tool to prioritize and select the company's actions. The main goal to be achieved in the scope of this dissertation, is the estimation of the ROI Farfetch may have from performance projects. In fact, there are several formulas to calculate ROI (Botchkarev et al., 2011), and the one to be applied in this context is given by equation 2.1.

The two elements to be estimated are both the initial investment cost, and the cost reduction obtained with such. The approach followed to measure the costs of the investment is the assessment of the travelling expenses and the necessary human resource allocation (hours dedicated by the team multiplied by the labour costs per hour). Calculating the possible benefits is indeed a more challenging task. According to the proposed formulation, they derive from the cost reduction obtained by improving operational performance. This formulation was preferred since one cannot observe a direct proportional relationship between the operational performance of a partner, and Farfetch's direct outcome of increase sales at a given moment. For example, at a certain point in time, if a customer is placing an order, the order will be placed whether or not being allocated to an optimal partner - on an operational point of view. However, what one should measure is the impact of inadequately serving the customer on that experience, hence the cost saving would derive from decreasing the number of orders fulfilled inappropriately.

It is necessary to investigate the degree to which operational issues represent increased resource allocation on both partner and customer service, plus estimating the customer compensation costs per operational issue. In the context of this dissertation, is also the estimation of the long term impact, by understanding whether it is visible a retention rate variation between customers who suffered from such issues versus those who did not, as to offer an additional measure of how the operational performance can represent a decrease of revenue in the long term - since CLV depends on the retention level. Therefore, the cost of operational problems is to be estimated by calculating:

- How much is Farfetch currently spending on compensations for the final customer;
- Excess of internal resource allocation in service operations, such as Customer and Partner Service;
- The degree of revenue losses in the long term, by multiplying variation in retention rates by the average customer lifetime value.

The benefits would be then the estimation of how many of those costs could be saved by helping a partner performing better after a project.

- **Performance Projects**

As to properly explain the degree to which performance projects can provide better operational set-ups, a brief introduction of their purpose is given. Plus, a description of the steps followed in these consulting activities is also provided. The need to include performance projects in the Fulfillment Development activities, derived from the current inability of Farfetch to personally and directly act on the order fulfillment processes, as to control the quality and guarantee the homogenization of the processes across the organization. Even if a lot of information on how to conduct fulfillment operations within Farfetch, there are always issues on the individual level of a partner, that can only be tackled if properly addressed and thought of.

The Fulfillment Development team tries to identify (with combined efforts from other internal teams, who are dedicated to partner integration and support) struggling partners, and offers them the possibility to board on a performance project. If all parties agree on the terms, the project is divided in the following stages:

- **Internal Deep Dive:** All the information about logistic organization (both on storage and shipping strategies), current operational metrics status and order volumes, is gathered and studied by the team.
- **Pre-requisites collection:** Additional information may be needed, therefore the partner is contacted in order to gather that information on an internal level - note that Farfetch is an intermediary, and only has the information needed to conduct operations within the marketplace.
- **Personal Visit:** The responsible consulting team visits the partner, and personally observes the internal processes whilst collecting data, whenever necessary (data types can be, for examples, processing times and headcount per process). Besides, there is also a discussion

about prioritization of project moments, as to align the needs of the partner with those of Farfetch.

- **Problem Solving:** When returned, the team must then process the data collected. This follows an identification of the main pain points/inefficiencies of the partner, and respective root causes. A plan of action is also established to address the highlighted problems, and to give an indication of the expected results.

- **Monitoring:** After applying the recommendations, it is necessary to closely follow the obtained results, as to either adjust the plan of action, or evaluate *quick-wins* and the given solutions. A control stage is always necessary for both addressing the consulted partner with the recommended solutions and, on a different level, to collect valuable insights for forthcoming projects.

Chapter 4

Methodology

This chapter offers a description of the methodology followed to describe and evaluate the phenomenons - direct and indirect costs (which can be also understood as long term impact), associated with inefficient operations conducted by Farfetch's partners. These costs will then be placed against the costs of implementing a performance project on a partner, as to evaluate the ROI a project may generate in the future, and prioritize the actions - project selection, of the responsible department. The division undertaken in this chapter is as follows:

1. Direct Costs: description of the methodology followed for identifying and evaluating the direct costs per operational issue - i.e., by measuring both the customer compensation costs and extra resource allocation due to an increase of contacts per orders with fulfillment issues.

2. Indirect Costs: through the utilization of two different approaches of a PHM, customer retention variation factors will be studied and quantified by means of a decrease on CLV. Additionally, the approach to calculate the expected CLV is to be provided in this section. Finally, it will be exposed how can an operational issue of an order may affect a next purchase from a first-timer, which represents an absolute loss of acquisition costs;

3. Performance Projects ROI Model: since being important to estimate the future state of a partner on an operational level - for ROI estimation purposes, the methodology for forecasting both the sales (quantity in units) and operational metrics is provided. Finally, it is also explained how the operational cost of a partner may be estimated with and without a performance project, to estimate the potential ROI.

Please refer to Figure 4.1, which provides a summary of the aforementioned methodology.

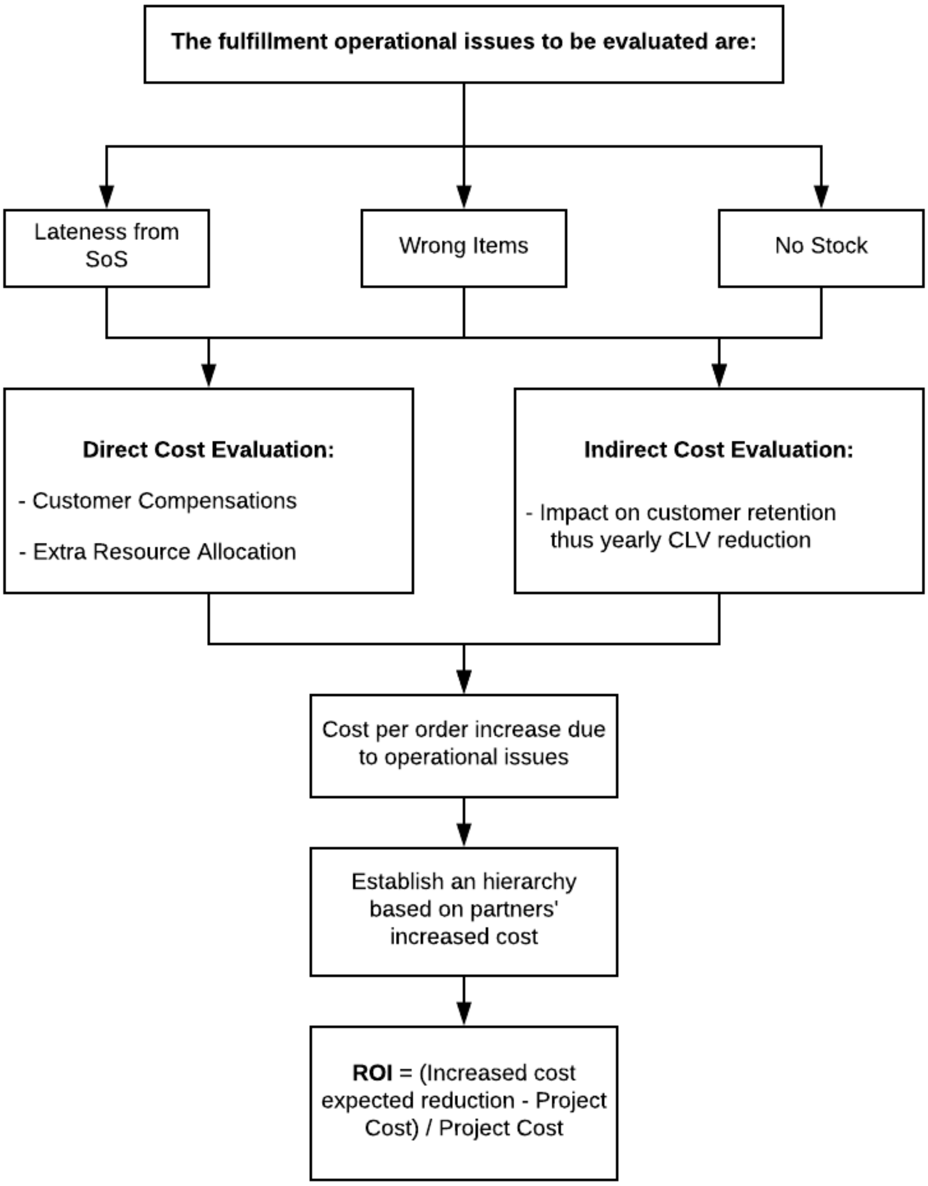

Figure 4.1: Methodology process

To conclude, the data collected to perform the above mentioned analyses comprised the years of 2017 and 2018, except for those that were run for evaluating particular cases in which the data was either not available or too extensive [1]. The resources (programming languages and software) used for data extraction, preparation and modelling were: SQL Server, Python, R Studio and Google Big Query.

[1] For the analysis of No Stock lost sales, and contacts per order other horizons were considered.

4.1 Direct Costs

How can one evaluate the outcome operational performance has on an online intermediary like Farfetch? There are two sides one shall analyze.

On one hand, to which extent does the partner's operational performance excellence drive more sales. On the other hand, can one be more cost efficient if guaranteeing a higher service quality?

As to understand the first approach - direct implication on revenue, it is important to explain how an order is currently allocated. Whenever the selected item is available in more than one partner, a duplicates algorithm runs to select which partner is best to allocate such order. In fact, one of the rules in the algorithm is indeed the historical operational performance of the partner. However, let us consider the following situation:

- An item is available at partner A and B;
- If prior rules tied them both, one reached the level of tie-breaking through operational score. Then, note that partner A holds better operations than B (measured by the operational metrics explained in the previous section);
- The order is shipped from partner A.

One may now understand that for a given time - the time of purchase, holding better operations does not mean that Farfetch will benefit in terms of increased revenue, since whether from partner A or B, the purchase would have always happened. Notwithstanding this, there can be a repercussion from having selected partner A if its level of operation is still somehow under target:

- Partner A sent a wrong item to customer C;
- Customer C, besides contacting customer service, returned the item and was further compensated for this mistake;
- Partner A did not cover the totality of these transactions;
- There is an increased risk of customer C not engaging with Farfetch in the future.

As presented above, the last two points do represent a negative repercussion of fulfillment operational issues - to what cost inefficiencies due respect. Even though one must aim for zero defects, it is also reasonable to understand that once speaking of fulfillment operations conducted by partners (humans), it is incredibly challenging to aim for 100% faultlessness. However, it is again legitimate to provide consultancy and proper tools to perform better, operations-wise, since the negative impact on the organization may be felt in terms of customer compensation costs, excessive resource allocation on customer/partner services and ultimately decreased retention rates.

In the following section a description of what Direct Cost from operational issues can be understood as, and how were they calculated, is to be provided. To evaluate them, there was a holistic gathering of information regarding the internal definition of what can be understood as an issue, plus what costs can be directly associated with it. As given in section 3.1.2, the operational metrics consistently monitored are:

- Wrong Item
- Speed of Sending (*SoS*) over one and two days (net values)
- No Stock

Hence, an operational issue occurs whenever one of these events takes place.

The division of the following sections within the direct costs methodology, is concordant with the study and evaluation of the different groups of direct costs, which are given bellow:

- **Customer Compensation Costs:** Refunds of item value, shipping fees and further compensations (the last can be bound to goodwill/retention actions, namely price reductions, vouchers, etc.);
- **Contacts per Order:** A higher volume of operational issues felt by the final customer, derive an increased rate of contacts per order. These contacts can have their source on the partner side, or on the final customer.

Since the methodology to evaluate the Customer Compensation Costs was distinct per operational issue, the organization of that section will be per operational issue. Contrastingly, only one section will be provided for the Contacts per Order cost group, since the analysis was constructed on a equal fashion for all issues.

To conclude, another cost evaluation was performed in the context of Direct Costs, since it proved to be relevant for the business, even though not being included in the final model. Such evaluation was a *Lost Sales* analysis, in which one inferred whether the customer tried to buy the same product after an operational issue of availability or accuracy - i.e., a No Stock or a Wrong Item event. The relevance of the analysis is to investigate the resistance a customer has on attempting a purchase of the same item, once the belief can go two ways - either the customer is strongly inclined to engage again with Farfetch for that specific product (disappointment from previous experience), or he is truly determined to get that specific item.

4.1.1 Customer Compensation Costs

What is the cost of a late order? And of shipping an incorrect item to the final customer? Plus, how can one evaluate the direct cost effect of stock unavailability?

This section helps on providing the methodology to evaluate the cost implications for Farfetch of these problems - namely those related to customer compensations after suffering from these fulfillment operational issues that lay under the responsibility of a partner.

4.1.1.1 Wrong Item

The compensation costs for wrong item events involve the following: a) shipping costs of the original item, since the return process is under a free return policy (hence, the shipping of return is not considered as a compensation); b) value of the item (it may occur that the item is not returned or not accepted back by the partner, so these situations must be accounted for in this study); c) further compensations, namely for goodwill/retention actions. These costs are primarily supported by Farfetch, however after negotiating with the partner who sent the order, there will be a recovery of a certain percentage - given by RR.

On Figure 4.2, the process underlying the evaluation of refund costs per wrong item received, as well as an indication of which transactions are involved in the process, can be observed.

In fact, one also had to evaluate the following situation: *What if someone tries to buy the same item again? And, if so, may it be compensated?*. Refer to Figure 4.3 to understand the evaluation process. The main difference from the process described on Figure 4.2 lies under the action of matching the price of the second purchase attempt with the first one. Once speaking of a marketplace, it is expected to encounter different prices for the exact same item, except from those that are compulsory marked with the brand's recommended price - hence, these are fixed-priced / geo-priced [2] items.

The complexity of this methodology, by virtue of the high volume of data, was to indeed isolate the problem of a wrong item. The refund data includes not only the exchanged value per record, but also the reason underlying each transaction (not all of them have to happen on the same date). That is why a single order with a wrong item can appear several times (as independent observations) in the data-set. What distinguishes each observation, the reasons, are circa 5000. There is some degree of standardization, since the volume of refunded orders is significantly higher. However, for the same order, the attribute *Real Reason* is the same for every observation - and this is discrete to 100 values, which makes it less complex to isolate the refunded orders due to wrong items. Refer to Table 4.1 to get an overview of how the data looked like.

Table 4.1: Example of the Refund data-set for Wrong Item analysis (reduced attributes)

Order ID	Reason	Real Reason	Value Paid $	Value Received $
10017	Shipping	Wrong Item / Size	50	47
23567	Wrong Item	Wrong Item / Size	350	350
10017	Wong Item	Wrong Item / Size	800	0

It is to note that only real reasons such as sizes, accuracy and damages were valid reasons for a wrong-item related refund. Nonetheless, some orders' refunds were not linked to a wrong item real reason, if some identification failed/ was changed. Therefore the process described below was followed to evaluate these refunds:

1. Identify orders that went under a refund process;

2. Of such orders, identify those that had a return due to a wrong item based on the categories identified above;

[2]Whenever a specif brands demands for its items to be sold by the stock owners (in this case, the boutique partners), for a given value per geographical location, then these items are marked as geo-priced.

3. If not returned and still had a refund due to wrong item, save these orders to quantify the expenditure whether entering or not on a return process;

4. Find, for the returned orders, if the combination *User ID + Product ID* was bought again and, if so, infer whether they have entered a refund process.

5. Further identify observations in the refund data-set that contained a real reason like those identified as for wrong items, but were not found in the orders data-set. This is to collect the maximum amount of information as possible.

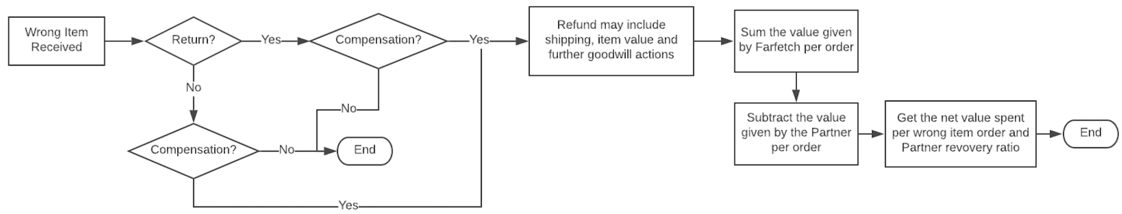

Figure 4.2: Wrong item refund costs evaluation with or without return

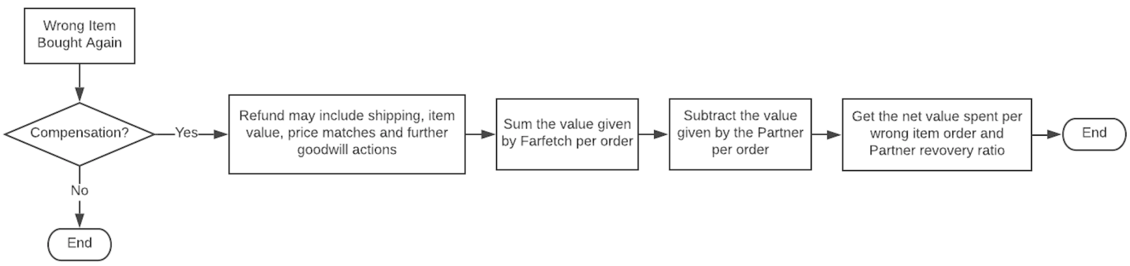

Figure 4.3: Wrong item bought again refund costs evaluation

To conclude, for the wrong items bought again, a verification of availability to fulfill a second order was undertook, as to understand whether the following purchase did not happen due to stock issues - the item did not exist anymore, or purely due to the fact that the customer did not want to re-purchase the item.

4.1.1.2 Speed of Sending *SoS*

The total lead time of an order is composed by the sum of the *Speed of Sending* and *Time in Transit*. Hence, lateness on the partner side is measured by *SoS*, whereas on the courier side is given by an extended *Time in Transit*.

To find which orders were found to be affected by lateness and went under a refund process, one had to find among the main and transactional refund reasons, which ones can be associated with true lateness. After consulting relevant stakeholders the main refund reason related to lateness is labeled as: *"Slower than customer expectations"*, hereafter mentioned as SCE. The head of the refund table, filtered for such problem would look like that given in Table 4.2:

Table 4.2: Example of the Refund data-set for SoS analysis (reduced attributes)

Order ID	Reason	Real Reason	Value Paid $	Value Received $
10345	Shipping	Slower than customers expectation	50	0
13998	Remove Shipping	Slower than customers expectation	0	50

The agreement shared with the partners as the target *SoS net* is of under two days, hence a late order on the partner side is one that has a *SoS net* higher than the target. However, if an order was indeed late, an evaluation of the given expectation is to be performed. Plus, since the lead time is further composed by the *Time in Transit*, investigating the discordance between its average value and the average value for the late ones, is also a necessary measure.

For evaluating if one did not meet the expectation provided to the customer by the time of checkout, the EDD of these orders was studied, and 70% of them failed with the agreement. Furthermore, the average *Time in Transit* of SCE was compared with the mean value for orders that can be viewed as "good" - i.e., not returned due to wrong items, not refunded, not canceled and were received (isolate *No Stock* events).

An ideal methodology for evaluating deviations on SoS (net and gross) would be that of modelling the empirical distribution this variable follows, since one could not find a known distribution to fit the data.

In fact, circa 20 different attempts were made to investigate whether the empirical distribution function of the gathered data could be fit to a common one, to facilitate the study of deviations. The goodness of fit of a statistical model describes how well it fits a set of observations, and in this particular case, the Kolmogorov-Smirnov(KS) test was used as a way to determine if the two samples - the SoS data and a common distribution, are significantly different from each other. However, as said before, the p-value was always zero, hence never higher than the established threshold of 5%. Due to time limitations, the strategy of observing whether the mean values of SoS (gross) for good orders was smaller than that for those identified as late, was followed in order to proceed with the classification. On Figures 4.4 and 4.5, the density plots of SoS (total) can be observed for SCE orders, and *"Good"* ones.

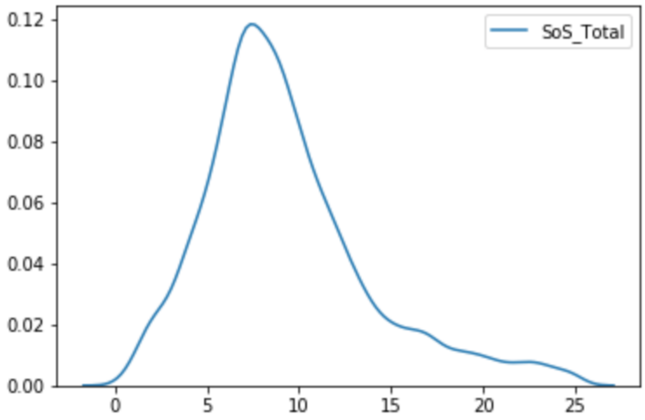

Figure 4.4: Density plot: SCE orders gross SoS

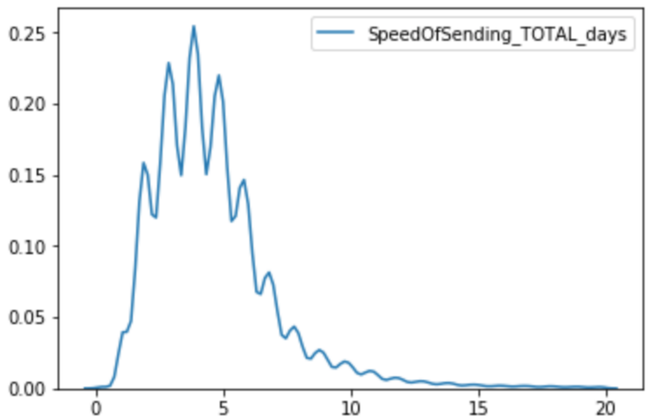

Figure 4.5: Density plot: *"Good"* orders gross SoS

After observing the distribution of SoS of these orders, it is understandable that modelling the empirical distributions to compare whether the means were significantly different would be complicated due to the shape of the function for *"Good"* orders. Hence, the mean values of SoS Gross, SoS Net, Time in Transit and Lead Time (all given in days) were calculated per order type (SCE, *"Good"*, and Further Evaluated), and are given on Table 4.3. Indeed, the SoS (both gross and net) is the metric that most diverges from the Good orders, which allows to say that lateness was mainly imposed by the partner (and not the courier, to the same extent).

Following this, the net value paid by Farfetch per late order (due to partner fault) has to be found. For that, the steps illustrated on Figure 4.6 were followed. It is to note that the values exchanged were mainly due to shipping refunds (hence mainly under 50$).

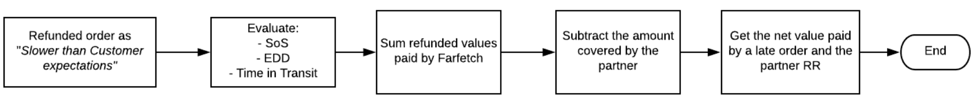

Figure 4.6: *Speed of Sending*: refunds evaluation process

At last, after removing all the previously identified observations - both refunds of *"Slower than customer expectations"* and Wrong Items, there was still a great percentage of orders that had *Free shipping* as a refund reason. Figure 4.7 provides a bar chart with the top ten identified refund reasons, in terms of volume of orders, that went through such refund process:

Figure 4.7: Top ten refund reasons after Wrong Item and Slower than Customers Expectations observations removal, x-axis: number of orders

To understand whether these orders - the Further Evaluated, were refunded not because of purely goodwill actions, but also due to lateness, a filtering strategy was performed:

- The Lead Time of these orders has to be larger than the EDD promised at checkout;
- The SoS (net) under two days condition had to be violated;
- The refund value of these orders had to be smaller than a certain threshold, to analyze only reasonable values for shipping costs refunds.

If the orders/refund values contained these three conditions, then they were gathered and the density plot of SoS gross can be observed in Figure 4.8:

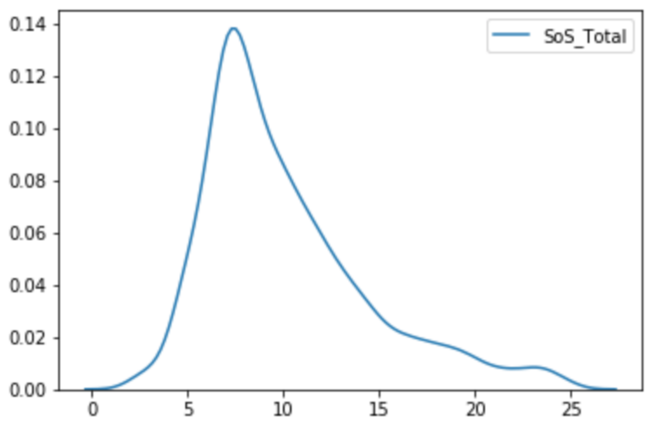

Figure 4.8: Density plot: gross SoS for further evaluated orders

In fact, the shape is similar to that observed for the *"Slower than customer expectations"* orders, and the mean values, also observed on Table 4.3 are also comparable, and significantly larger than the "Good" ones. Hence, these further evaluated records were diagnosed as late (due to partner fault), and the refund value can be understood also as a compensation cost.

Table 4.3: Mean Values obtained for "speed" metrics (in days) on Good, SCE and Further Evaluated Orders

Order Type	SoS Gross	SoS Net	Time in Transit	Lead Time
SCE	10.108	2.922	4.570	14.678
Good	4.580	0.852	3.058	7.638
Further Evaluated	10.128	2.330	5.385	15.513

To conclude, it is also observable in terms of average values, that the *Speed of Sending* exerts a higher influence on the Lead Time of an order, comparatively to the Time in Transit. Hence proving the relevance of controlling this operational metric on a partner level, to offer the final customer with the desired consistency on delivery experience.

4.1.1.3 No Stock

A *No Stock* event is an operational issue that dues respect to product unavailability. In the context of Farfetch, a partner must indicate whether the product is available after a customer places the order. It is natural to understand that not all orders will be fulfilled by the partner selected for that order, due to stock unavailability. However, Farfetch will try other ways for that order to happen - namely, initiate an Item Swap process, or suggest an alternative product to the client. If no alternative is found, the customer is notified, and given a voucher of a symbolic value - this is understood as an absolute No Stock event.

The most automated and common alternative measure after a No Stock event is indeed an Item Swap. What happens is basically a replacement of the formerly designated partner, for another who holds inventory of the purchased item. It was explained before how the same item can have several prices, since there are different partners selling the same product, therefore Farfetch has to cover the item value difference in case the alternative partner holds a higher price.

But how can the direct costs of a No Stock be evaluated? Since studying compensation cost did not make sense in this analysis - as an absolute No Stock event generates a voucher and the client is immediately refunded with the value of his order, it was necessary to tackle this problem in a different way. Two strategies were followed:

1. How many successful Item Swaps happened after a No Stock event, and how many items were marked with a higher price, to calculate the amount paid by Farfetch with Item Swaps - hence calling this expenditure as an indirect customer compensation cost;

2. How many of these No Stock events were truly a *lost sale*, i.e., there was complete unavailability to fulfill the order before the placement of the order.

- **Item Swap costs**

For the first point, it is relevant to further introduce the concept of an Item Swap. As indicated before, whenever the firstly selected partner fails to provide with the ordered item, a second partner will be selected to do so - it must be internally indicated that such partner has stock. In fact, the customer does not know about this internally developed process, the fulfillment just takes longer. Plus, a second No Stock (an so on) could technically happen if the sequent partners would also fail to hold stock. A successful Item Swap is that in which the order is sent. So at this stage the following values/calculations were recorded:

- Total number of No Stock events
- Total number of Item Swaps that followed
- Successful Item Swap percentage
- Value differences between *"original"* item and the Item Swap
- Absolute cost of an Item Swap

- **Lost Sales**

Not every No Stock event can be considered as a lost sale. This is the hypothesis to verify under this part of the methodology. In fact, primarily due to the complex information system that manages the stock and different levels of system integration (partner - Farfetch), one can not expect to have a perfect sync between the point-of-sales and the stock update. Plus, since there are partners who do not separate their offline/online stock, there is always the risk of selling an item offline after the order was placed online. However, Farfetch only has access to such information when the stock levels are updated by the partner. This results in what may be identified as a *lost sale*, since there would be no fulfillment options after the partner indicates a zero stock level for that particular item, and no other partner owns stock for an Item Swap. The methodology and assumptions for aggregating all these observations were:

- Isolate the effect of integration deficits (Farfetch fault), by analyzing only those that have stock sync; [3]
- To further mitigate Stock Sync delays/effects, a margin of 30 minutes was given before the order creation date and after the No Stock date;
- Only partners with reasonable No Stock percentages were analyzed - i.e., those which values did not reach an upper-bound of 5 % (80% of the partners' No Stock percentage falls under such threshold);

[3] Stock Sync is an information system that is dedicated to the integration of inventory levels between the partner's systems (WMS; ERP, etc.) and Farfetch.

- The sum of stock updates between the order being created and the No Stock date had to be negative, hence reunited the conditions of a *lost sale*.

Finally the data utilized to report the results of this analysis was gathered from 6 months (ending in March 2019) and they will be shown on the following chapter.

4.1.2 Contacts per Order

If the customer faces any problem on his journey with Farfetch, particularly with fulfillment operations, there is an increased likelihood of an increased volume of contacts on customer service. Plus, since those in charge of fulfillment are the partners, it is also expected to observe a higher level of support from partner service, as the operational issues increase.

To measure the impact of fulfillment operations issues in terms of contacts per order, it is of first attention to clarify what is considered to be a contact; a direct attempt to communicate with either customer/partner service can be an e-mail, a phone call or an interaction in the internal information system dedicated to follow these kind of issues raised from our stakeholders (customer and partner).

Impact can then be translated into how many more contacts were established whenever an issue occurred - lateness, No Stock or Wrong Item, to be consistent with the previous analyses, comparatively to the number of contacts generated with a *perfect order*. These last orders are the baseline on which impact will be placed against.

The *perfect orders* must be those that did not have any problem concerning operations - were not late (SoS net under two days), returned due to Wrong Item or a No Stock / Item Swap event. Plus, orders in transit were not included in the analysis.

Since the data-base that gathered this kind of information was recently implemented in Farfetch, the time-period analyzed encompassed only two months of activity. Such reality can indeed affect the analysis, once it would be beneficial to have at least one year of activity, mainly to observe how peak seasons and other special occasions would influence the number of contacts per order - to get a more approximate value of this metric/ its variation with issues.

4.2 Indirect Costs

Recalling the second stream of analysis - long term impact on sales, the analytic approach was that of understanding how the baseline survival function of a Farfetch customer would be affected by operational issues. Survival can be understood as retention, which is the word commonly used in Business-to-Customer contexts.

Retention in Farfetch can be understood as inter-purchase times smaller than one year - hence, an "alive" customer on the 20th of January 2019 is one whose last purchase had to be on a date equal or after the 20th of January 2018. On the contrary, a churned customer is one whose inter-purchase times are higher than a year - i.e., after observing a purchase, one can not observe any more purchases one year onward (or until the "alive" period ends).

Two hypothesis for evaluating the impact operational issues - No Stock, Lateness and Wrong Item, have on retention were established:

First hypothesis: The inter-purchase times after an operational issue are larger, hence the risk of making a purchase at a given time is smaller for those customers. The approach to study this hypothesis will be hereinafter mentioned as PHM-01.

Second hypothesis: An operational issue has a negative impact on retention, meaning that for a given time horizon, if a customer suffers from operational issues, there is an increased risk of churn at that moment. Similar to the above, this approach will be henceforth mentioned as PHM-02.

Survival analysis is a methodology for examining and modelling the time it takes for events to occur, hence focusing on the distribution of survival times. The Proportional Hazard Model (PHM) is a semi-parametric regression model for studying survival data, with the main purpose of estimating the influence that a given set of covariates has on the variable to be described as time-to-event. For PHM-01, that variable is the inter-purchase time, whereas for PHM-02 it is the time until churn. This method was selected since it allows to study several covariates simultaneously. Plus, in contrast with widely applied parametric survival analysis models, PHM introduces a favorable feature as it can provide a non-parametric estimate of the hazard function - hence its form is not pre-constrained. Since the baseline hazard rate function for Farfetch's customers was not known, PHM was the method selected for evaluating the influence of covariates.

The covariates in the case of this study were: No Stock Events, Wrong Items, and Lateness through SoS net. The time of study comprised two years of activity - 2017 and 2018. The methodology for constructing the models for PHM-01 and PHM-02 was considerably different, hence an explanation of all the followed steps will be given for both. The models were developed resorting to both R and Python programming languages and the retention effects are to be translated into CLV variation. For estimating the current CLV of an average Farfetch customer, a sub-section 4.2.3 provides a detailed view over how that value can be obtained and furthermore be affected by retention levels.

4.2.1 PHM-01: Inter-purchase time

For assessing PHM-01, the event of interest is whether that customer will purchase again in the future with inter-purchase - i.e., the next purchase will happen in a time-horizon smaller than the end of the study which in this case, was the 31st of December of 2017. If the value is 0, it means the observation is right-censored - no further purchase was observed until the end of study. Plus, the time-to-event data is the inter-purchase time if the event value is 1 - i.e., the time till next purchase. However, if the event value is 0, the time-to-event is difference between the purchase date of that order and the end of the study. Each line of the data set did respect to a purchase observation, hence even if the same customer appeared several times in the data set, his observations were independent from each other. The set of covariates were dummy variables, in the sense that per observation, it was indicated whether a given operational issue occurred in that purchase. A look of the prepared data-set is provided on Table 4.4.

Table 4.4: Data-Set example for PHM-01

UserID	Purchase Date	Wrong Item	No Stock	SoS <1 day	Time until next Purchase	Will Repeat Purchase
102	01-11-2017	0	0	1	61	0
125	23-12-2017	1	0	1	5	1
505	09-10-2017	0	1	0	0.5	1

The whole data set was engineered, besides the User ID and Purchase Date, since all the covariates, event and time-to-event data were not given on this final form. The event data is the column "Will Repeat Purchase", whereas the time-to-event column is "Time until next Purchase". In terms of interpretation, UserID 125 will buy again on the 28th of December 2017 since the event data equals 1, whereas for UserID 102, no further purchases were observed, hence a 61 days "Time until next Purchase". The effect of the covariates - No Stock, SoS <1 day and Wrong Item will be shown on Chapter 5. Selecting SoS net under one day was done since this is becoming the new target for the organization, hence it would be valuable to investigate its effect at this stage, comparatively to SoS net under 2 days, which has been considered the target for quite some time.

4.2.2 PHM-02: Survival time

For PHM-02, similarly to PHM-01, the data of analysis comprised only purchase data and covariates relative to 2017, even if for analyzing the event it was necessary to look into 2018. However, the data-set developed was considerably different in terms of engineered variables, since the analysis also differed in purpose. In fact, if measuring the time-to-churn is now the event to analyze, the data must contain information on an individual level - i.e., each line dues respect to the observations of a given customer, hence treating each customer as an independent one.

The event to be considered is "Churn", and the time to event describes the time between the first and last purchase observed in 2017 of a given customer. To know whether the customer has churned - to translate that into an indication of 1, purchase data of 2018 had also to be investigated. If a given customer made his last purchase on 2017 (so no purchases observed in 2018), then the "Churn" variable is 1. Additionally, if inter-purchase times larger than 365 days, the customer is also considered to be churned. For example, a customer makes a purchase on the 2nd of January of 2017 and then on the 5th of March of 2017; if the next recorded purchase is on the 4th of May of 2018, this customer is marked with a 1 on the "Churn" variable, and his Survival is that between the 2nd of January and the 5th of March. Contrastingly, if for a given customer it is observed a first purchase on the 3rd of September 2017, a second on the 4th of December of 2017, and a third on the 16th of January of 2018, he is marked with a 0 on the "Churn" variable, and his survival interval is between the first and second purchase and the covariates are relative to those transactions. Observe an example of the data-set used for PHM-02 on Table 4.5.

The covariates are the same as those evaluated on the previous model, however, on the previous they take binary values on the order level, and in the last they account for the number of times a certain issue was observed on the customer level. In terms of effect analysis - to be given in the Results Chapter, one can understand that for PHM-01 the deviation from the baseline is based on

Table 4.5: Data-Set example for PHM-02

UserID	Number of Purchases	Wrong Item	No Stock	SoS <1 day	Survival	Churn
102	2	0	0	1	300	0
125	10	1	0	2	50	1
505	2	0	1	0	100	1

the value of 1 that each covariate takes, whereas for PHM-02 is based on the value being different than 0. It is also relevant to indicate that "special" customers - such as personal shoppers, re-sellers, or those that purchased more than 500 times were removed since they could be adding an outlying effect on the study.

On a final note, using PHM in the context of Farfetch was an attempt to help on the description of the impact operations have on the final customer, and the results must be carefully analyzed and interpreted, like any results obtained with any other analytic tool.

4.2.3 Expected Customer Lifetime Value

While collecting and constructing the data for the previous analysis of indirect costs, one was enabled to estimate the expected number of purchases a given customer makes on a year period. In fact, this is a necessary estimate to understand what could be the CLV (yearly value) for an average Farfetch customer, as to quantify the retention deviations introduced by operational issues. To prepare the data for this analysis, outlying users were removed - namely personal shoppers and re-sellers, and a year of purchases per customer was stored to be further investigated. It was also necessary to extract the company's average order value (AOV) for the years of 2017 and 2018, and the expected number of purchases per customer. Plus, recognizing that not all customer have a basket size of a single unit, the AOV was obtained for the average basket size, which for the analyzed customers, it took a value of approximately 1.6 items per purchase. An example of how the data used for estimating the average number of purchases a given average customer does with Farfetch looked like, is given on Table 4.6. It is to note that the values provided are fictitious.

Table 4.6: Data-Set example with fictitious values for estimating the yearly number of purchases per average customer

Purchase Number	Absolute Frequency	Relative Frequency	Cumulative Frequency
1	355645	0,3	0,3
2	224567	0,2	0,5
3	101109	0,05	0,55

The estimation of the number of purchases was then obtained through equation 4.1:

$$NrPurchases_{customer,year} = \sum_{i=1}^{n} PurchaseNumber_i * RelativeFrequency_i \tag{4.1}$$

where:

i is the Purchase number (1, 2 ...n), i.e., the purchase number i of a certain customer

n is the higher number of purchases recorded for a single customer, on a year period

As for the expected monetary value those purchases represent, it was necessary to multiply the Relative Frequency of a given amount of purchases (Purchase Number) per the Farfetch AOV. The resulting value was an estimate of the traded value per customer on a year period, which is identified by tv_{1year} in the context of this dissertation.

Finally, these point estimates have to be aggregated to estimate the Farfetch's CLV. The CLV formulation for a discrete time horizon is the one to apply in the context of this problem, and the necessary elements to estimate such value for the average Farfetch customer are given by equation 4.2:

$$CLV = \sum_{t=0}^{T} \frac{(p_t - c_t) r_t}{(1+i)^t} - AC \tag{4.2}$$

where:

p_t is price paid by a customer on time t

c_t is the direct cost of servicing a customer at time t

r_t retention rate at time t ("being alive" at that time)

AC is the customer acquisition cost

i is the firm's cost of capital

T is the time horizon for the estimate

The discrete time to be considered is one year, since that is the horizon used within the organization to observe retention, and all the previous information was gathered following that principle, hence T = 1. The value of p_t is obtained by multiplying the previously calculated variable, tv_{1year}, by the Farfetch's sales percentage - since the AOV accounts for the item values (the price paid by the customer) it is necessary to weight this value against the average Farfetch sales commission (once a marketplace, Farfetch shares its revenue with the partners). Hence, p_c is given by tv_{1year} times the average Farfetch Commission.

For the cost of capital (i), the cost of acquiring a customer (AC), and servicing it at time t - c_t is the cost per retained order (CPRO), the marketing department provided the values of the three metrics for the year of 2018. It is to note that the cost of acquisition is approximately 5.5 times higher than the cost of retaining a customer, confirming the importance of ensuring continuous service quality and customer satisfaction. In fact, after calculating the average number of purchases per average customer per year period, one concluded on an expected value of four, hence the CPRO (indicated as c_t) must be multiplied by three.

The yearly customer retention (for an average Farfetch customer) was obtained through the PHM-02 PHM analysis; it was observed that the risk of churning, for a customer who has not yet churned until the day number 365, was 70%. Hence r_t takes the value of 0.7.

4.3 First timers vs. Non-first timers churn

Since the analytic technique used to evaluate the long term impact of operational issues - particularly PHM-02, did not permit the inclusion of users who only purchased once, an investigation of an aggravated churn effect comparatively to those with multiple purchases (at least two) on a year time was performed - starting on the 1st of January of 2017. The relevance of such study lies under the fact that acquiring a customer is considerably more expensive than the cost per retained order, hence if finding that an operational issue felt by a first timer is an aggravating churn factor, such churn percentage increase may be multiplied by the customer acquisition cost, to assess the loss generated by the issue on a first timer. The underlying hypothesis was that an operational issue would affect - in terms of churn percentage level, a first timer on a larger scale comparatively to non first timers.

To prove the veracity of the hypothesis the following data was gathered and studied:

- First Timers Data:

  - Number of first timers;

  - Percentage of first timers who churned - total amount of purchases during the study was only one;

  - Of those who churned, how many had: a Wrong Item, a No Stock event and an SoS over one day (to be consistent with the previous analyses), and divide this number per the total number of non first timers who had each of those fulfillment issues;

  - Percentage of first timers who churned after an operational issue.

- Non First Timers Data:

  - Number of non first timers - total amount of purchases mandatorily higher than one;

  - Percentage of non first timers who churned - the event defined for PHM-02 took the value of 1, meaning the customer has churned during the study;

  - Of those non first timers who churned, how many had: a Wrong Item, a No Stock event and an SoS over one day, and divide this number per the total number of non first timers who had each of those fulfillment issues;

  - Percentage of non first timers who churned after an operational issue.

The aggravating effect on churn rate after an operational issue, when comparing the quality of the user (first timer or not), will be given on Chapter 5.

4.4 Performance Projects ROI Model

For estimating the ROI a performance project may represent for Farfetch on a future perspective, it is necessary to quantify the cost of holding poor operations at a given time, thus inferring the financial magnitude of incorrect fulfillment at a partner level. This is due to the chosen formulation for evaluating ROI having included the cost reduction with improved metrics. If the cost per fulfillment operational issue is known, then for a given partner, one can simply multiply the volume of orders that fall into each issue by the cost per order of such issue, to evaluate the cost of the partner without a project. Hence, if a partner improves operationally with a performance project, the volume of incorrectly fulfilled orders should decrease, allowing for the calculation of a new cost - and, consequently, a cost reduction.

4.4.1 Operational metrics and sales forecast

Recalling the fulfillment operational metrics evaluated in this context: SoS net under one day and two days (percentage over sent orders), Wrong Item over Returns percentage and, finally, percentage of No Stock events over the allocated orders, it is necessary to forecast the operational metrics and the sales volume (in units) of all the partners who cooperate with Farfetch - since the operational metrics are always calculated as a percentage of the allocated orders.

The model to be developed has to be able to contain future estimations on both the growth level of the partner - in terms of allocated orders and traded value, and its operational metrics. That is due to the need to estimate future cash flows related with cost decrease with improved operational metrics, as to estimate the ROI of a project, per partner.

In fact, after being advised by relevant stakeholders that forecasting the operational metrics was a very challenging and not yet internally performed task, it was decided to not use a forecast technique at this stage. However, in terms of expected sales volume (in units), it would be valuable to proper estimate how they would be in the near future.

After observing the sales pattern of the overall Farfetch marketplace, both a trend (positive growth) and seasonality (marked by November peaks, for example) are present. On Figure 4.9, the sales values (in units) from 2017 until 2018 are represented graphically.

Figure 4.9: Average sent orders - values between April 2017 and March 2019

Peak seasons result from sales seasons and other special occasions, such as Black Friday and other special discount periods. The forecast model has to be able to capture these events, and for that reason a model developed by *Facebook*- Prophet: forecasting at scale (Taylor and Letham, 2018), was used in the context of this dissertation to estimate the sales of the partners for the next three months, once it allows to insert conditions such as the shape of the trend (linear or logarithmic), special dates known in advance (like the Black Friday), among others.

4.4.1.1 Defining conditions on the forecast

Since operating with considerably different partners - in terms of sales volume and value, stock units and depth, geographical location, entry dates on the marketplace, etc., it is expected to have notably distinct sales observations between partners. The necessary inputs to forecast the sales volume (in units), for the next 6 months [4], of the universe of partners by means of Prophet were:

- **Type of growth:** Logistic or Linear; For this context, logistic growth was chosen after a few trials with the other option did not produce very pleasing results, especially for boutiques with a reduced number of observations. For the logistic growth it is necessary to establish a capacity (upper bound value). The capacity was defined by multiplying the yearly expected growth by the average number of orders of the previous year, both values being of the overall marketplace in case the number of observations was smaller than 18 months, or the sales values of the specific partners if having more than 18 months.

- **Seasonality:** Fourier Order or Customized for a period, which in this case the period selected was the yearly seasonality - that could be either Farfetch's seasonality or the partner's, if the number of observations would be higher than 1.5 years.

The difference in selecting the seasonality to integrate in the forecast was due to the existence of partners whose sales point observations were under 1.5 years, which produced unsatisfactory forecast results. For these partners the seasonality was defined as: the average number of Farfetch orders of a given month (number of orders divided by the volume of partners), minus the average number of Farfetch orders of the last six months, divided by the second factor. This produces a percentage deviation per month, on the mean number of orders of that month comparatively to the last six months, as observed on Figure 4.10.

As noted on the previous image, there are already given values for the seasonality factor for forecast months. The mean number of orders of the overall marketplace, both calculated and future projected ones (based on the criteria of multiplying the expected growth by the average number of orders of the last 12 months), are given on Figure 4.11.

To conclude, some forecast results produced negative values for those partners whose observation volumes were higher than 18 months. To overcome that, one followed the same strategy defined above, for the partners who had less than 1.5 years of observations - average Farfetch values were used. Finally, it is to note that partners who have less than 6 months of activity were excluded from the analysis, since besides producing unreliable results, these partners are also not relevant for the context of Performance Projects investment valuation - these are still in their learning curve of on-boarding in the marketplace.

[4] Six months was the period selected because that is the control phase of a performance project, hence estimating ROI accounting that period was considered to be a relevant internal metric.

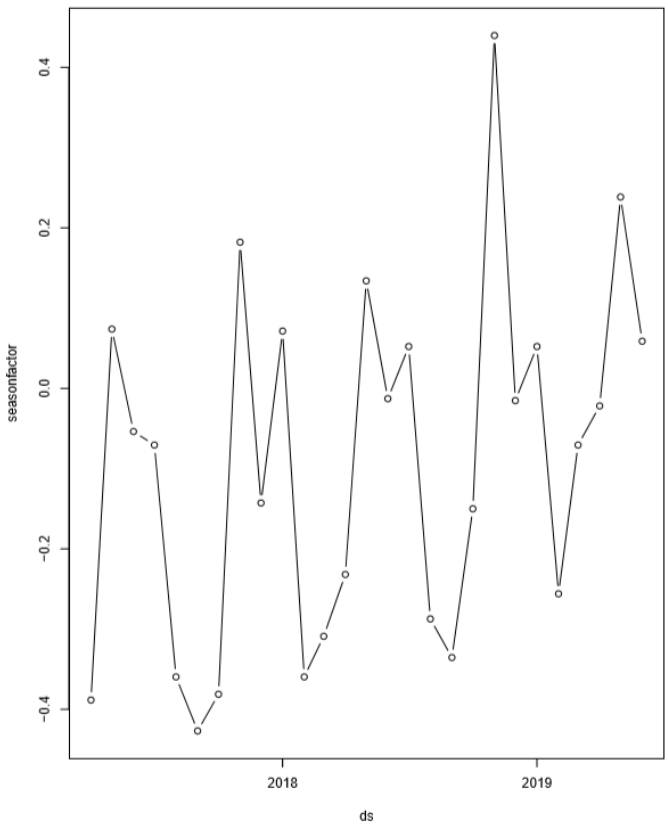

Figure 4.10: Farfetch seasonality as a percentage of the last six month's average number of orders

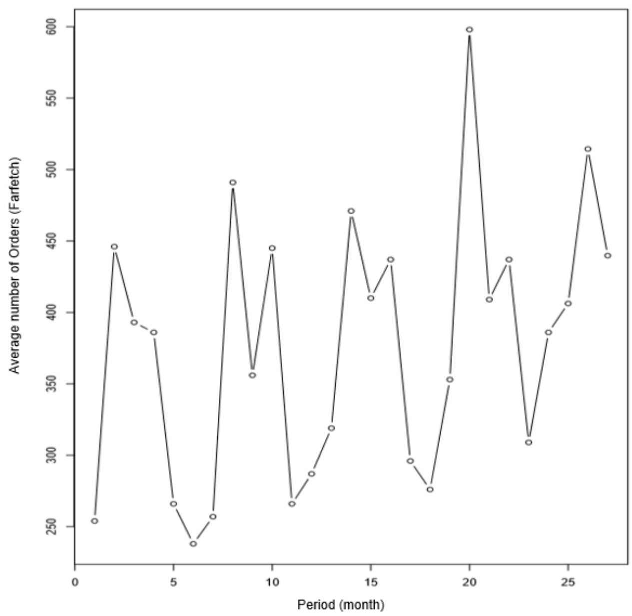

Figure 4.11: Farfetch average number of orders: actual and forecast values

4.4.2 Prioritization Rules

Since the main goal of the present dissertation is to estimate the potential ROI Farfetch may have with a performance project, let us recall the chosen formulation given by equation 4.3:

$$ROI = \frac{(CurrentProcessCost - NewProcessCost) + OtherBenefits}{CostsofImplementingtheProject} * 100 \tag{4.3}$$

The results acquired from the previous analyses must be aggregated to determine the expected cost per operational issue, hence allowing the design of a cost matrix of operational issues (with values of cost per issue, per order).

Knowing both the costs of each operational issue as well as the operational metrics of a partner (% of SoS net < 1 and 2 days, % of Wrong Item and % No of Stock) per given period, the operational cost of a given partner on such period can be calculated by equation 4.4:

$$OperationalCostPartner_{ij} = \sum_{k} \%Orders_{kij} * CostOfIssue_k * Orders_{ij} \tag{4.4}$$

where:

i is the index to identify a partner

j is the index to identify a month-year combination

k is the index to identify the operational issue - No Stock, Speed of sending (net) over 1 day and 2 days, and Wrong Item.

In fact, since a percentage of the ATV is given to Farfetch, as a penalty for performing under target according to Service 4.0. rules, this value should be used to balance the current cost of operational issues. On the other hand, if performing better than the target, the %ATV given back by Farfetch should also be accounted for.

The hypothesis of analyzing the cost reduction according to these two methods, allows for the Fulfillment Development department to understand the estimation of cost reduction on an isolated manner, since Service 4.0 is considered to be an investment on the partner, thus not necessarily a cost; plus, it was not defined under the responsibility of the department for which this model is being defined, therefore corroborating the necessity of knowing both values.

Similarly to equation 4.4, if effects of Service 4.0. are accounted for - which can be the parcel of *OtherBenefits*, the cost of the operational issues of a partner on a given period are calculated by equation 4.5:

$$OperationalCostPartner_{ij} = \sum_{k} \%Orders_{kij} * CostOfIssue_k * Orders_{ij} j + \%ATV_{ij} \tag{4.5}$$

What must be defined as well, is how a comparison should be established between projects (and subsequently partners). Since the initial investment costs are variable among partners, both the comparison and prioritization should be conducted in terms of potential cash flows derived from either the current cost of partners' operations, or the potential cash flows obtained through improving the current operational metrics by a given percentage. The cash flows derived from such improvement can be calculated trough equation 4.6, for a particular partner on a given period:

$$CashFlow_{ij} = OperationalCostPartner_{ij} - OperationalCostPartnerWithProject_{ij} \tag{4.6}$$

For prioritizing based on the cash flows method presented above, the suggested improvement percentages have to be transversely equal and applied to all partners - i.e., an input value of the model is the expected reduction (% reduction) to be applied on the current partners' metrics. Plus, an indication of the deviation between the current partner metrics and the targeted ones is to be provided - since the target varies from partner to partner, depending on the Tier they belong to. With this, one can also observe the estimated cash flows if a partner would match the designated target. Appendix B further helps the reader on understanding the different operational targets per partner Tier (or OKRs per Tier and geographical region)

On a partner level, the model should be able to provide an expected ROI. Once analyzing only one partner at a time, it is possible to input an estimated initial investment cost, because at this level,the particular characteristics of a partner: such as region, size, logistic set-up, etc., can be more easily estimated.

To conclude, the ROI potentially obtained through a performance project on a particular partner, should be provided including and excluding the Service 4.0. cash flows.

Chapter 5

Results

The results are to be provided in an analogous manner as the methodology, hence the division of the present chapter is as follows:

1. Direct Costs per operational issue: Wrong Item, Speed of Sending and No Stock;
2. Indirect Costs:
   - PHM-01 and PHM-02 results;
   - CLV variation per operational issue through the results of PHM-02 - therefore, indirect cost per Wrong Item, Speed of Sending (net, over one and two days), and No Stock;
   - First timers vs. Non-first timers churn.
3. Performance Projects ROI Model: Practical Example

5.1 Direct Costs

The results of the Direct Costs analyses will be given per operational issue, as a value of $/order. These costs must finally be aggregated - as well as the Indirect Costs, in a cost matrix, which is to be included at last in the Performance Projects ROI model.

5.1.1 Wrong Item

As described in sections 4.1.1.1 and 4.1.2, the direct costs resulting from Wrong Item issues were defined based on both Customer Compensation Costs and Contacts per order. Lost sales will not be used as a component of direct costs, after analyzing with relevant internal stakeholders that this effect should preferably be allocated in terms of future impact on revenue - and not a direct cost. However, since the PHM includes this operational issue as a covariate, the result obtained from that analysis will the be one to input on the indirect costs matrix, to avoid cost over-estimations/ overlaps.

As indicated before, the analyzed horizons were of 2017 and 2018. The overall volume of refunded orders during this period was approximately 104.5 thousand, and those related to Wrong

Item issues represented circa 22% of these - hence approximately 23 thousand, which in monetary figures equaled a net cost of roughly 934 thousand US Dollars. The net cost was obtained by subtracting all the recovered refund values from all the initially traded value by Farfetch for such refunds. In terms of summarized results, Table 5.1 gives all the recorded values per category of Wrong Item refund. It is to note that for the Wrong Items not returned, a likelihood of being refunded could not be found, since there was no indication in the overall Farfetch data base whether a Wrong Item was not returned, except for the refund case.

Table 5.1: Values recorded from the refund transactions due to a Wrong Item fulfillment issue

Order Type	Refund Likelihood	Net Cost	Net Cost per Refunded Order	Net Cost per Wrong Item Order	% of Wrong Item Refunds	Recovery Ratio
Returned	1/4	724 k$	42 $	12,6 $	77,5	78,9 %
Not Returned	N/A	93 k$	35 $	1,6 $	10	41,2 %
Bought Again (after return)	1/3	117 k$	73 $	2 $	12,5	54 %

Since the operational metric followed on the partner level for Wrong Items, is the percentage of returns due to wrong items, hence the value to be aggregated in the cost matrix is 12,6$, which is the net cost per Wrong Item Order (for a returned order type as indicated on Table 5.1).

In terms of contacts per order, the values obtained are given on Table 5.2:

Table 5.2: Contacts per Order: values for a Wrong Item fulfillment issue

Order Type	Avg Contacts per Order	Cost per Order	Cost Uplift
Perfect Order	0,63	1,97 $	-
Returned Wrong Item	9,38	29,27 $	14,83

To conclude the analysis for the Direct Costs of a Wrong Item issue, the Lost Sales results are to be provided. Remembering the refund per order type, with particular attention to the *Bought Again*, it is relevant to indicate that for the analyzed horizon, 16% of the customers who returned a Wrong Item, bought the exact same product again on the next purchase - and out of these, 29% received a refund (understood as a customer compensation cost) for this transaction. However, what about those 84%? Analyzing the stock values for the items returned due to a Wrong Item, one found that 20% out of those 84%, were cases in which stock of the initially wanted item still existed. Notwithstanding this finding, one can not promptly say that these 20% of cases, were indeed lost sales, although a previous experience gone wrong can be an indicator for not attempting a second purchase of the same item.

5.1.2 Speed of Sending *SoS*

Similar to the approach followed to evaluate a Wrong Item issue, the refunds generated as a customer compensation for a lateness issue - that should be linked to the partner level, were aggregated to obtain a cost per order. Along this value, other relevant metrics are given on Table 5.3.

Table 5.3: Values recorded from the refund transactions due to a Late Order (partner level)

Order Type	% of Refunds	Net Cost	Net Cost per Refunded Order	Net Cost per Order with SoS net >2 days	Recovery Ratio
Slower than Customer Expectation	5	76 k$	16,5 $	1,4 $	44 %
Free Shipping	3	46 k$	14 $	1,4 $	1 %

The value of 1,4$ per order being equal for both order types is due to the need of generalizing the cost per late order. Hence the strategy was that of summing the net cost of these refunds, and divide it by the volume of late orders - Speed of Sending net over two days, observed between 2017 and 2018. Finally, for this fulfillment issue the contacts per order analysis results can be consulted on Table 5.4.

Table 5.4: Contacts per Order: values for Speed of Sending net

Order Type	Avg Contacts per Order	Cost per Order	Issue Cost uplift
Perfect Order	0,63	1,97 $	-
SoS net >2 days	1,69	5,29 $	2,68
SoS net >1 day	0,82	2,58 $	1,31

5.1.3 No Stock

The results obtained for the direct costs of No Stock fulfillment issues that can be considered for direct cost per order, were those related to the Item Swap analysis - which can essentially be considered as an indirect customer compensation cost covered entirely by Farfetch, hence a 0% Recovery Ratio. The Lost Sales will not be accounted for this cost, since not all partners reunite all the necessary conditions to meet the assumptions of the study, hence resulting on an over-estimation of the direct cost of this issue. However, for the Item Swap analysis, the results observed were:

- Percentage of successful Item Swaps after No Stock orders: 15,3%;
- Total value lost on item price differences covered by Farfetch: 1,3 million USD;
- Value lost per Item Swap order: 54$;
- Value lost per No Stock order (Total value lost over all recorded No Stock events): 8,5$.

Indeed, not following the strategy of evaluating refund net costs, was due to encountering only 2,8% of Item Swap orders and 0,2% of No Stock orders (effective, without Item Swap) under a refund process (between 2017 and 2018). It is to note that other interesting statistics were found during this and the Lost Sales analyses: in general, approximately 33% of customers who suffer with a No Stock event did not engage again with Farfetch. Plus, the Lost Order analysis allowed one to conclude that 15,6% of the No Stock events can be considered an effective lost sale, which represented a loss close to 14,5 million US Dollars - this value was obtained through multiplying the likelihood of a lost sale by the number of No Stock events between 2017 and 2018, and finally by the weighted AOV for that period.

In terms of contacts per order, the values can be consulted on Table 5.5:

Table 5.5: Contacts per Order: values for No Stock events

Order Type	Avg Contacts per Order	Cost per Order	Issue Cost uplift
Perfect Order	0,63	1,97 $	-
No Stock	1,98	6,17 $	3,12

5.2 Indirect Costs

In this section the results for both hypotheses analyzed through a PHM will be provided to the reader. For the resulting findings, a translation of retention variation into a financial measure of the cost per incorrectly fulfilled order will be given, by means of estimating CLV variation. Additionally, the results of the churn analysis of first timers will be provided, however these will not be considered for the cost matrix per operational issue on the indirect costs domain.

5.2.1 PHM-01: Inter-purchase time

May one recall the underlying hypothesis to be tested:

PHM-01: The inter-purchase times after an operational issue are larger, hence the risk of making a purchase at a given time is smaller for those customers.

The general results of the model, which included approximately 3 million purchase observations and 1.7 million events, can be observed on Table 5.6:

Table 5.6: Results for PHM-01 with 3 covariates

Covariates	**coef**	**exp (coef)**	**p value**	**coef lower 0.95**	**coef upper 0.95**
No Stock	0,33	1,39	<0,005	0,32	0,34
Wrong Item	-0,07	0,93	<0,005	-0,09	-0,06
SoS net >1 day	-0,08	0,92	<0,005	-0,09	-0,08

The output statistics can be interpreted as follows:

- **coef:** the beta coefficient - if positive, the effect on hazard is positive; contrarily, if negative, the hazard decreases;
- **exp (coef):** the multiplicative effects on the baseline hazard - if higher than one, there is a positive effect; if not, then a negative effect is to be observed;
- **p value:** statistical significance of the covariates - if smaller than the confidence level of 5%, there is no statistical significance to reject the null hypothesis - which is, the covariates do not exert an influence on the baseline hazard;

- **coef lower 0.95:** the lower limit of the coefficient, for a 95% confidence interval;
- **coef upper 0.95:** the upper limit of the coefficient, for a 95% confidence interval;

Plus, to evaluate the relevance of the model itself, the Likelihood ratio test was also a test statistic of the model. A p value of 0, proved the significance of the overall model.

While analyzing the results, one observed that the No Stock covariate actually exerted a positive influence on the baseline hazard - exp(coef) equals 1,39. This means that for a given point in time, the effect of a No Stock on a previous purchase indeed increases the risk of purchasing again - and with a shorter inter-purchase time. For the covariates Wrong Item and Speed of Sending over one day, the results were as expected according to the initial hypothesis - the risk of purchasing again decreases when these events are verified on the previous purchase.

A Kaplan Meier estimator for the analysis with given on Figure 5.1. It is to note that with a sufficiently large sample, this estimator may help one to visualize a fair approximation of the survival function for the population - in this case, surviving means not establishing a next purchase.

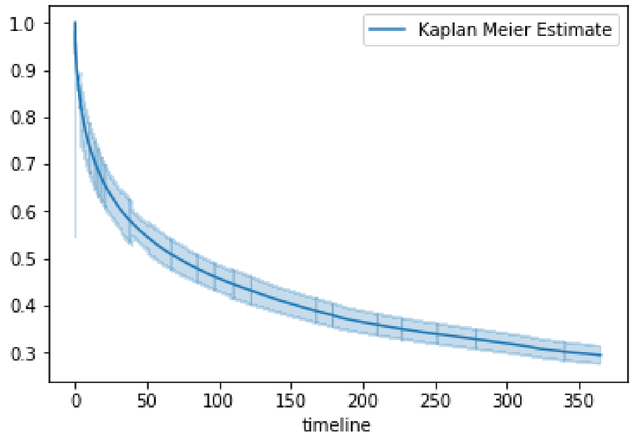

Figure 5.1: Kaplan Meier estimate of the baseline Survival Function - PHM-01 with 3 covariates

Yearly retention rate through this analysis is given by: S(t) = 1 - R(t); thus being 30% the value for a year (when t = 365 days), the retention for that period is 1 - 0.3, hence 70%.

Since the results from PHM-01 did not allow one to observe the desired results for one of the covariates - namely No Stock, the second approach results will be used to estimate the indirect costs of an operational issue. The second approach indeed tests the effect of covariates on a different manner, and the results are to be provided in the following section 5.2.2.

5.2.2 PHM-02: Survival time

The second PHM was developed to verify whether the effect on the baseline hazard - which in this case is the risk of churning at a given moment, was concordant with prior expectations. In fact, since this model aggregates the purchase observations per customer, the effect of fulfillment operational issues can be tested in a different manner. May the reader recall that in the previous model, every observation was representative of one purchase. Therefore, the set of purchases per user was being observed independently. Then, it is of interest to not only evaluate the effect a previous experience has on the one which immediately follows, but also observe how the general retention of a customer is affected by his set of purchases.

The results of PHM-02 can be observed on Table 5.7: Similarly to what was done for the

Table 5.7: Results for PHM-02 with 3 covariates

Covariates	coef	exp (coef)	p value	coef lower 0.95	coef upper 0.95
No Stock	0,07	1,08	<0,005	0,05	0,10
Wrong Item	0,17	1,18	<0,005	0,13	0,20
SoS net <1 day	-0,05	0,95	<0,005	-0,05	-0,05

previous model, it is pertinent to evaluate the relevance of the model itself, hence a p value of 0 proved the statistical significance of the overall model - test statistic for the Likelihood ratio test. The Kaplan Meier estimate of the survival function can be observed on Figure 5.2, and it is to note that the Survival likelihood at a given time S(t) is interpreted as retention.

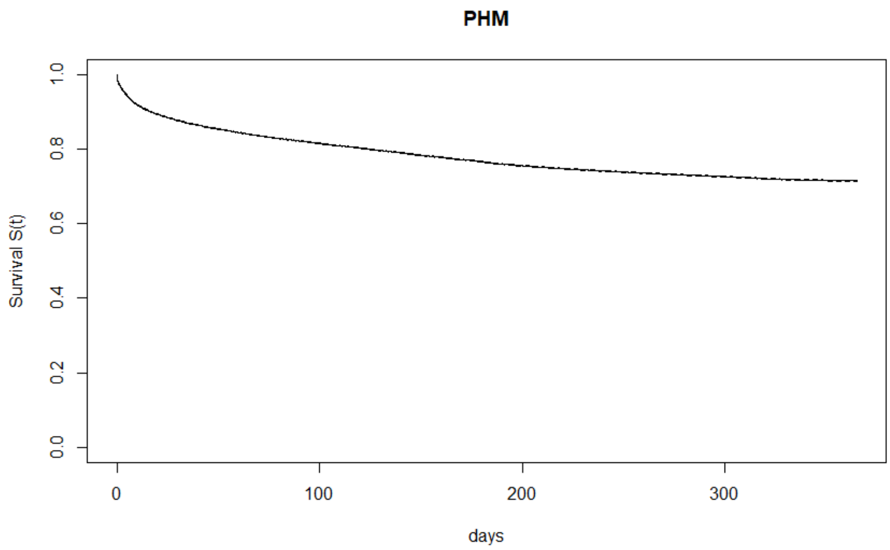

Figure 5.2: Kaplan Meier estimate of the baseline Survival Function - PHM-02 with 3 covariates

The results of No Stock and Wrong Item events both increasing the hazard - the risk of churning at a given moment if not having churn yet, and a SoS net under one day decreasing the hazard, is indeed aligned with the initial expectancy that a fulfillment operational issue negatively affects retention (it is to note that the rejected hull hypothesis is that the covariates do not exert any influence on the baseline hazard). Also, it is to note that the limit on t = 365 days validates a final retention rate of 70% (since the value for PHM-01 is 30%).

Once producing the desired results and being statistically significant - both on a covariates and overall model levels, it is necessary to further investigate if there is a violation of the assumption of proportional hazards. The theoretical assumption to verify is indeed the checking the proportionality of hazards, to understand if the fitted model adequately describes the data. Testing the proportional-hazards assumption for each covariate, is done by correlating the corresponding set of scaled Schoenfeld residuals with a suitable transformation of time (the default is based on the Kaplan Meier estimate of the survival function). The test statistic p, per covariate, is provided on Table 5.8: In fact, for a confidence interval with a 95% confidence level, the covariates No

Table 5.8: Results for PHM-02 - Testing the Proportionality Assumption

Covariates	p value
No Stock	0,091
Wrong Item	0,438
SoS net <1 day	0,000

Stock and Wrong Item prove to be statistically significant. However, the same is not verified for the SoS covariate - p value is 0. Due to time restrictions, nothing was done to further investigate the reasoning behind this value, however it is to note that several techniques can be done to test whether this problem may be solved, and they will be further discussed on Chapter 6.

5.2.3 Retention Effects on Customer Lifetime Value: application of PHM-02 results

The reasoning behind selecting the PHM-02 lies under the fact that the model produced the desired output relationship between the covariates and the baseline hazard, even if verifying that the proportionality assumptions was violated for the *SoS* covariate. Plus, the data was organized in a manner that every customer is being treated as an independent one - contrarily to treating every purchase as an independent one like on the PHM-01.

How can one translate retention variation into a financial metric of cost per operational issue, per order?

The coefficient of every covariate gives the indication of retention variation, since it represents the increasing or decreasing effect over the baseline hazard. Hence, for a given moment in time, it is expected that if a customer has not yet churned, the risk of churning at that moment is increased/decreased if having one of the fulfillment issues - therefore the baseline risk is multiplied by the resulting coefficient of the issue.

Recalling the formulation of CLV, given by equation 4.2, one observes that retention is one of the variables to be inserted. The results from PHM-02 allow one to obtain the retention rate variation per fulfillment operational issue, plus knowing that the baseline retention rate is 70%, the expected CLV variation per operational issue is given by Table 5.9:

Table 5.9: Covariates coefficients from PHM-02 translated into CLV variation

Covariate	Coefficient	Delta CLV
No Stock	0,07	2,86 $
Wrong Item	0,17	6,95$
SoS net >1 day	0,05	2,04 $

To conclude, this CLV variation has to be translated into a cost per order. If one understands that fulfilling a customer with one of the issues studied in this context, there is a risk of losing the expected Delta CLV in a year horizon. Therefore, the cost per operational issue on an order level is the one indicated on Table 5.9, because behind every order lies a customer who is expected to be affected - translated through the risk of negatively deviating its retention rate from the baseline.

5.3 First timers vs. Non-first timers churn

The financial effect of verifying a worsening effect on the churn rate - due to operational issues, can be estimated by multiplying the customer acquisition cost, by the worsening rate. In fact, as highlighted before, acquiring a new customer is 5.5 times higher than retaining a new one - in the context of Farfetch, that is. The results obtained through he methodology described on section 4.3, can be observed on Table 5.10.

Table 5.10: Results on worsening effects - First Timers vs. Non-first timers churn analysis

Churn Type	General Churn Rate	Churn with Wrong Item	Churn with No Stock	Churn with Lateness (SoS net >2 days)
First Timer	62,8 %	56,8 %	53,6 %	61,7 %
Non First Timer	8,4%	61 %	51,2 %	57,7 %
	Worsening Effect	**- 6,9 %**	**4,7 %**	**6,9 %**

5.4 Performance Projects ROI Model: Practical Example

The preceding results (excluding those from the *First timers vs. Non-first timers churn* analysis), allow for the establishment of a cost matrix for the fulfillment operational issues, given by Table 5.11:

Table 5.11: Cost Matrix of fulfillment operational issues

Operational Issue	Direct Cost	Indirect Cost	Total
Wrong Item	39,90 $	6,95 $	**46,85 $**
No Stock	12,70 $	2,86 $	**15,56 $**
SoS net >2 days	4,72 $	2,04 $	**6,76 $**
SoS net >1 day	0,61 $	2,04 $	**2,65 $**

Recalling section 4.4.2, the cost of the operational issues per partner, per given period, is dependent on both its operational metrics and the sales volume. Through equation 4.6, the expected cost reduction by improving the operational metrics, by means of a performance project, is possible to estimate. Equation 4.6 is given bellow:

$$CashFlow_{ij} = OperationalCostPartner_{ij} - OperationalCostPartnerWithProject_{ij}$$

As observed above, the cash flows equation 4.6 depends on the calculation of the cost of the operational level of a given partner in a designated period (without and with a suggested improvement). Also on section 4.4.2, it is explained how equations 4.4 and 4.5 can be used to estimate the cost of a partner who operates with a certain level of operational metrics (with or without considering the cash flows of Service 4.0., respectively).

For a partner whose current operational metrics (%) and sales volume are those given on Table 5.12, the operational cost of that partner without a project can be observed on Table 5.13 (equation 4.4 was used hence the Service 4.0. cash flow was not considered):

Table 5.12: Partner's operational metrics (%) values and sales volume in units per period

	Current Metrics				
Period	**Orders**	**SoS <1**	**SoS <2**	**NS**	**WI**
20193	7562	26%	84%	0,7%	3,0%
20194	7879	57%	95%	0,6%	3,7%
20195	25785	57%	95%	0,7%	3,7%

Table 5.13: Cost of a partner's operational issues for current metrics values

Period	Current Cost of Ops Issues
20193	$ 28 316
20194	$ 20 192
20195	$ 66 318

For the improvement percentage suggested on Table 5.14, one can obtain, again through equation 4.4, the cost of that partner if improving to the suggested level (by means of a performance project). The reduced cost is given on Table 5.15.

Table 5.14: Suggested Improvement percentage example values

Improvement Percentage			
NS	**WI**	**SoS <1**	**SoS <2**
60%	20%	10%	50%

Table 5.15: Cost of a partner's operational issues for improved metrics values

Period	Cost of Ops Issues with Improvement %
20193	$ 26 610
20194	$ 17 991
20195	$ 50 968

Through equation 4.6 it is possible to calculate how the difference between the current metrics and the suggested improved ones can be translated into a cash flow per period. On Table 5.16, the last two columns indicate the cash flows from the suggested improvement, including or excluding the cash flows (% ATV) of Service 4.0., respectively on the last two columns.

Table 5.16: Example Analysis of a particular Partner - Cash Flows with current and suggested improved metrics

			Current Metrics				Improved Metrics					
Period	**Orders**	**GMV**	**SoS <1**	**SoS <2**	**NS**	**WI**	**SoS <1**	**SoS <2**	**NS**	**WI**	**Improvement Gain**	**Improvement exc. Service**
20193	7562	$2 450 953	26%	84%	0,7%	3,0%	28%	88%	0%	2,4%	$-1 706	$6 872
20194	7879	$2 553 633	57%	95%	0,6%	3,7%	59%	97%	0%	2,9%	$-2 201	$4 183
20195	25785	$8 357 263	57%	95%	0,7%	3,7%	59%	96%	0%	2,9%	$-15 350	$13 900
20196	11524	$3 734 968	52%	94%	0,7%	3,8%	54%	96%	0%	3,1%	$-6 173	$6 899
20197	10940	$3 545 819	52%	94%	0,7%	3,7%	54%	96%	0%	3,0%	$-5 918	$6 493
20198	7805	$2 529 710	52%	94%	0,7%	3,7%	53%	95%	0%	3,0%	$-4 187	$4 667
20199	5831	$1 889 861	52%	93%	0,7%	3,6%	54%	95%	0%	2,9%	$-3 106	$3 508

Estimating the possible ROI of a performance project on partner is the event of interest. Therefore, if calculating the ROI for 3 periods ahead - hence by summing the cash flows generated through the improving gain, from June 2019 until September 2019, with an estimated initial investment cost of 7200$, the resulting values for ROI, including and excluding Service 4.0. are respectively: -326% and +150%.

Furthermore, the operational metrics deviation from the Tier target and its cost implications are provided. On Table 5.17, the column *Loss From Target Deviation* is placed next to the current cost of operational issues, to indicate the cash flows that could be saved if the partner would be performing on target, on a given period. In terms of metrics, the columns that indicate the target deviation percentages are also provided. If deviations are negative, the partner is over-performing according to the Tier he belongs to in that period, whereas if positive, these deviations are generating an increased cost for Farfetch (positive cash flows).

Table 5.17: Example Analysis of a particular Partner - Cash Flows from Target Deviation

			Current Metrics				Target Deviation					
Period	**Orders**	**GMV**	**SoS <1**	**SoS <2**	**NS**	**WI**	**SoS <1**	**SoS <2**	**NS**	**WI**	**Current Cost of Ops Issues**	**Loss from Target Deviation**
20193	7562	$2 450 953	25,7%	83,9%	0,7%	3,0%	54,1%	12,1%	0,0%	0,0%	$28 316	$14 765
20194	7879	$2 553 633	57,0%	95,2%	0,6%	3,7%	22,8%	0,8%	0,0%	0,0%	$20 192	$4 409
20195	25785	$8 357 263	57,5%	95,0%	0,7%	3,7%	22,3%	1,0%	0,0%	0,0%	$66 381	$14 523
20196	11524	$3 734 968	52,2%	93,9%	0,7%	3,8%	27,6%	2,1%	0,0%	0,0%	$32 521	$8 621
20197	10940	$3 545 819	52,0%	93,8%	0,7%	3,7%	27,8%	2,2%	0,0%	0,0%	$30 555	$8 296
20198	7805	$2 529 710	51,6%	93,6%	0,7%	3,7%	28,2%	2,4%	0,0%	0,0%	$21 925	$6 063
20199	5831	$1 889 861	51,7%	93,3%	0,7%	3,6%	28,1%	2,7%	0,0%	0,0%	$16 302	$4 622

Since a methodology to estimate the initial investment cost of a performance project was not developed, it is not possible to transversely input that cost on all partners automatically. Hence, since not using a ROI prioritization rule, the *Current Cost of Ops issues*, and the *Loss From Target Deviation* and *Improvement Gain* cash flows are used to establish a hierarchy between partners, by organizing them on a descending order, through any of those monetary values.

This prioritization rules are possible to apply due to the nature of their calculation. The current cost of operational issues describes the *"losses"* if the partner operate on their current (or forecast) level, hence one can observe the cost state without performing any project. Additionally, and

Performance project prioritization list example

Period	Partner	Current Cost of Ops Issues	Loss From Target Deviation	Improvement Gain
201908	A	14690	3568	3321
201908	B	12342	3217	2109
201908	C	9870	1997	1134

still not applying a suggested improvement gain, the loss from target deviation allows to observe the partners who are under-performing according to their level - which can naturally retrieve a different prioritization order comparatively to the current cost of operational issues. In a suggested improvement is transversely applied, the team can understand the potential of their projects on a cash flow level.

Finally, the model also offers the possibility of performing an individual ROI assessment of a partner, while testing multiple improvement scenarios and initial investment costs. Thus, the prioritization list becomes a tool to generically observe the universe of partners, or filter them based on certain characteristics - region, boutique or brand type, etc., or financial interests, whereas the individual analysis helps on further investigating the potential of the priority list.

Chapter 6

Conclusion and Future Developments

The main goal to be achieved was that of constructing a model that could address the need to prioritize performance projects, based on the expected Return on Investment each would be able to generate. In fact, since not all projects can be conducted with an equally attributed initial investment cost and, due to time restrictions, a proper estimation per partner could not be established, the strategy followed the prioritization according to the cash flows expected to be obtained - calculated through an estimated cost reduction, by improving the fulfillment operational issues by an input percentage transversely applied to the whole universe of partners.

It can be concluded that the project goals were indeed met, although with some limitations. On a point of view of Direct Costs , it would be necessary to further extend the Speed of Sending analysis - namely by determining the empirical distribution of the Speed of Sending (both net and gross values) of Good Orders and those found to be classified as late. With such a description, it would be possible to investigate if these orders' SoS were significantly different on a statistical point of view. Additionally, studying the Lost Sales due to No Stock events for the partners whose characteristics did not comply with all the undertook assumptions, would be valuable to insert this cost on the overall cost matrix per operational issue, per order. As for Wrong Items, one only included the cost of returned wrong items into the cost matrix, due to the fact that this is the only order type included in the Service 4.0. However, it would be beneficial to understand if other order types - for example, those which were Bough Again, may or not be included in the matrix.

With respect to the Indirect Costs analyses, there are indeed further actions that could be conducted to enhance the quality of the results. On one hand, for the H1 PHM, it would be valuable to study - by means of applying other analytic tools, why would a No Stock event produce such an interesting result of increasing the risk of a next purchase. Plus, validating the proportionality assumption for the whole model would be necessary - however, since one decided to follow the strategy given by H2 PHM, the validation was undertaken only for this scenario. Towards a H2 PHM discussion, even though the results were concordant with the initial belief, it would be interesting to perform one of the following strategies, since for one of the covariates - SoS net under 1 day, the proportionality assumption was not observed:

- A way to accommodate non-proportional hazards is by means of building interactions between covariates and time into the Cox regression model - hence building a model with time-dependent covariates; These models do not accommodate only a single baseline hazard function, but the necessary ones to describe how it changes throughout time;
- The variable SoS could be changed by another categorical variable - such as EDD. With this strategy one would be analyzing whether an order was received (or not) within the provided expectation to the final customer. However, with this strategy, it would be necessary to further study the influence SoS has on Lead Time, hence concluding about the likelihood of violating EDD due to SoS.

The technique chosen to describe the survival function of an average Farfetch customer, was indeed an attempt to provide insightful results that could be translated into a financial measure. To further validate the results without changing the model by means of the to above-mentioned techniques, one could apply a cross-validation tool. For instance, partitioning the data set into two parts - one comprising 70% of the data for fitting and prediction purposes, and the other 30% remained untouched for cross validation, to understand if the results of the prediction would be satisfactory. In addition to this, the organization could study these variables influence on retention by means of other analytic tools, since this would be a good approach to observe whether the results obtained with this project are proven to be consistent with others. Additionally, since not all customers belong to the same Tier[1], the value of a customer can differ significantly for a year period. Likewise, retention levels could also be contrasting on a Tier level comparison, as well as the coefficients found on the survival analysis, if this would to be ran per Tier. Furthermore, it is to note that proving a relationship between the risk of observing the events of interest and the covariates tested, may not be enough to explain causality. One technique that could be used to address this endogeneity issue, could be a Difference-in-Differences approach in which for example, a Tier would be studied in the following manner: first, from the selected Tier, there would be a selection of customers that have not been affected by operational issues - the control group, and then gather a group of customer who have suffered from operational issues (although before the test they must have not suffered from any), therefore the effect of the issue could be compared between groups, before and after the issue occurred (refer to the works of Bell et al. (2017) and Parker et al. (2016), for further understanding this approach).

On a final model definition point of view, since this dissertation's analyses comprised the years of 2017 and 2018, it would be important to automate all the previous analyses, therefore allowing one to update the cost matrix per operational issue on a timely manner. Furthermore, a predictive analysis for the operational metrics would be valuable to better understand what would be the future state of a partner on such level.

As a final conclusion, it is observable on the improvement gains including Service 4.0. cash flows, that the ROI was found to be negative - and such finding was observable for more partners as

[1]A Tier is defined according to the cumulative expenses a customer has on a year period. Therefore hierarchies are defined whether a customer reaches - or surpasses, a certain monetary threshold, which defines the levels between Tiers.

well. Even if out of the scope of this dissertation to study the Service 4.0., this negative result may somehow indicate that the investment levels on the operational excellence of a partner, may not be adjusted to the cost of the operational inefficiency, which could be a potential risk for the bottom line of the organization on an operational level. However, enhancing and protecting operational excellence is viewed as an investment on the partners and, ultimately, on the organization itself - because offering high quality service on a consistent fashion to the final customer is of utmost and inestimable importance.

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Appendix A

Farfetch Incentive Service: Service 4.0.

SERVICE 4.0

Operational Excellence Program

FARFETCH

HOW IS THE **INCENTIVE PROGRAM** CALCULATED?

CALCULATION: Up until now, we've considered Speed of Sending and No Stock separately on our incentives and penalties. From now on, the new Incentive Program will combine your Speed of Sending and No Stock results in a matrix to determine your final payout.

Find your monthly Incentive Service value within the matrix using your position of Speed of Sending & No Stock.

→

Use this value to calculate your monthly payout as follows:

- Incentive Service value x ATV *

The STORM Dashboard includes your Speed of Sending and No Stock results. As soon as we launch the Incentive Program, this dashboard will be upgraded to help you tracking your performance.

We have 2 different matrices depending on your order volume per month.

* We acknowledge the higher impact of a penalty for lower volume of orders.

MORE THAN 76 ORDERS / MONTH

		No Stock Percentage								
	%	0 - 0,25	0,26 - 0,5	0,51 - 0,75	0,76 - 1	1,01 - 1,5	1,51 - 3	3,01 - 5	5,01 - 7	7,01 - 100
Speed of Sending SLA	99,51 - 100	1,30%	1,00%	0,80%	0,40%	0,20%	0,10%	-0,25%	-0,50%	-0,70%
	98,51 - 99,5	0,90%	0,60%	0,30%	0,20%	0,10%	0,05%	-0,35%	-0,75%	-0,90%
	97,51 - 98,5	0,60%	0,30%	0,20%	0,10%	0,05%	0,00%	-0,40%	-1,00%	-1,10%
	96,51 - 97,5	0,40%	0,15%	0,10%	0,05%	0,00%	-0,10%	-0,50%	-1,25%	-1,50%
	95,01 - 96,5	0,30%	0,10%	0,05%	0,00%	-0,10%	-0,20%	-0,60%	-1,50%	-1,90%
	90,01 - 95	-0,05%	-0,15%	-0,20%	-0,25%	-0,30%	-0,50%	-0,75%	-1,75%	-2,30%
	70,01 - 90	-0,30%	-0,40%	-0,50%	-0,60%	-0,70%	-0,80%	-1,00%	-2,25%	-2,70%
	0 - 70	-0,50%	-0,70%	-0,90%	-1,10%	-1,50%	-1,90%	-2,30%	-2,70%	-3,00%

UP TO 75 ORDERS / MONTH

		No Stock Percentage								
	%	0 - 0,25	0,26 - 0,5	0,51-0,75	0,76 - 1	1,01 - 1,5	1,51 - 3	3,01 - 5	5,01 -7	7,01 - 100
Speed of Sending SLA	99,51 - 100	1,30%	1,00%	0,80%	0,40%	0,20%	0,10%	0,00%	-0,10%	-0,70%
	98,51 - 99,5	0,90%	0,60%	0,30%	0,20%	0,10%	0,05%	-0,10%	-0,20%	-0,90%
	97,51 - 98,5	0,60%	0,30%	0,20%	0,10%	0,05%	0,00%	-0,15%	-0,45%	-1,10%
	96,51 - 97,5	0,40%	0,15%	0,10%	0,05%	0,00%	-0,10%	-0,20%	-0,50%	-1,50%
	95,01 - 96,5	0,30%	0,10%	0,05%	0,00%	-0,10%	-0,25%	-0,30%	-0,55%	-1,90%
	90,01 - 95	0,00%	-0,10%	-0,15%	-0,20%	-0,20%	-0,40%	-0,45%	-0,60%	-2,30%
	70,01 - 90	-0,15%	-0,35%	-0,40%	-0,45%	-0,50%	-0,55%	-0,60%	-0,65%	-2,70%
	0 - 70	-0,50%	-0,70%	-0,90%	-1,10%	-1,50%	-1,90%	-2,30%	-2,70%	-3,00%

EXTRA INCENTIVE for orders sent in < 1 DAY

Applies in addition to the matrix conditions

% Orders with NET SOS < 1 day	Incentive
0% -79%	0% Packaging Cost Refunded
80% -89%	25% Packaging Cost Refunded + 0,2% ATV
90% -100%	100% Packaging Cost Refunded + 0,4% ATV

CONDITIONS:

1. You have received 5 or more NPS responses that month, and the average Packaging rating equals or is higher than 4,5 (out of 5).
2. If you have received 4 or less NPS responses, you will still be eligible, regardless of the packaging rating.

WRONG ITEM RULE

To be eligible to all kinds of incentives (based on the matrix and extra incentive for orders sent in less than 1 day) it is mandatory to comply with the conditions below.

# of Returns	% Wrong Item *
0-5	No Threshold
6-25	50%
26-75	10%
>= 76	6%

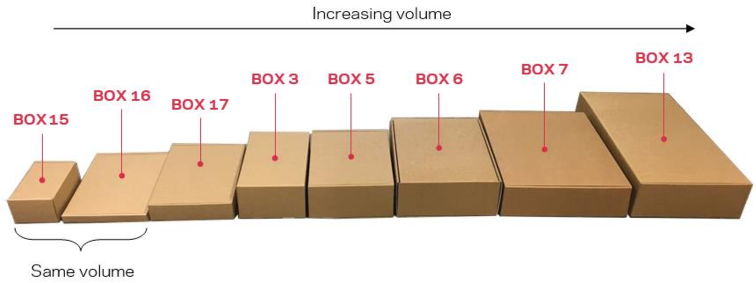
* Wrong item = returns marked by customers as Faulty, Wrong Item and Wrong size.

PACKAGING INCENTIVE

Please note this incentive is contingent to the Wrong Item rule.

Partners will **receive 0.04% of their monthly ATV back** when they follow Farfetch Recommendations or use a more suitable package for 85% of their orders.

This incentive is based on the packaging that you actually use compared to the packaging recommended by Farfetch on STORM at the packaging stage.



Note: Box 14 is missing but it is the biggest one.

The picture shows the various Farfetch Boxes that could be recommended to you.

WHAT ELSE CHANGES?

Service 3.0	Service 4.0
Packaging cost waived per order if order NET SOS < 1 day	New <1 day extra incentive allows for part of packaging costs to be refunded depending on the % of orders with NET SOS < 1 day
Penalty to support customer shipping cost for orders with NET SOS > 2days	No longer applicable
10£ No Stock voucher charged in most cases	10£ No Stock vouchers charged for every order cancellation
10% of canceled item's price charged in case of high No Stock levels	No longer applicable
Free Returns Fee waived if the monthly No Stock rate < 0,75% + compliance with the Wrong Item Rule	Free Returns Fee will never be waived, regardless of your results

METRICS

- **ATV - Actual Transaction Value**

  the aggregate of Sales Prices for all orders less any Cancellations and Returns and Sales Taxes.

- **Speed of Sending (SOS)**

  % of orders sent that month with SOS < or = to 2 Net*. Value corrected after Exceptions are solved.

- **No Stock**

  % of items cancelled by No Stock that month, over all sold items. Value corrected so No Stocks manually changed to Farfetch fault are excluded.

- **% of orders sent in less than 1 day**

  % of orders sent that month with a SOS < or = to 1 day Net*. Value corrected after Exceptions are solved.

- **NPS packaging rate average**

  average of all packaging rate responses given that month (NPS Date).

  *Net SOS excludes the time spent in STORM steps: payment verification & AWB. We also exclude weekends and holidays.

HOW TO MAXIMISE YOUR INCENTIVES

Important aspects to keep in mind:

- Make sure that each month you comply with the Wrong Item Rule

– if you don't comply to the rule, you will not be eligible for the incentives.

**wrong items will be calculated until the end of the following month to allow time to process the orders.*

- Avoid paying additional cost such as the No Stock vouchers by keeping your stock levels up to date.
- Use the No Stock and Speed of Sending to monitor your percentage of ATV
- If your Packaging Rate is over 4.5, you will get an extra incentive if you have shipped at least 80% of your orders in less than one day.
- Always aim to ship 90% or over in less than one day, to enjoy the best incentive. This incentive refunds 100% of your Packaging Costs and 0.4% of ATV.

When calculating the incentives you will need the following information:

1. ATV
2. Number of Orders Sent
3. Speed of Sending (%)
4. Speed of Sending < 1 day (%)
5. No Stock (%)
6. Number of No Stock Items
7. Packaging Rate
8. Number of NPS
9. Wrong Item (%)
10. Number of Returns

EXAMPLE

STEP 1: GATHER YOUR MONTHLY RESULTS

- **Monthly ATV:** 539505,00€ (120 orders)
- **Orders Sent:** 1923
- **SOS%:** 99,24% **SOS% < 1:** 81%
- **Monthly SOS:** 80% (80% orders shipped in 1 working day)
- **Monthly NS%:** 1,00% **NS Quantity:** 18
- **Packaging:** 4,80
- **NPS:** 10
- **Wrong Items sent:** 200 returns arrived, 10 listed as wrong item sent (5% of the returns were due to wrong items sent to the customers, i.e. within threshold.)

STEP 2: CALCULATE YOUR BASIC INCENTIVE FROM THE MATRIX

MORE THAN 76 ORDERS / MONTH

		No Stock Percentage								
Speed of Sending SLA	%	0 - 0,25	0,26 - 0,5	0,51 - 0,75	0,76 - 1	1,01 - 1,5	1,51 - 3	3,01 - 5	5,01 - 7	7,01 - 100
	99,51 - 100	1,30%	1,00%	0,80%	0,40%	0,20%	0,10%	-0,25%	-0,50%	-0,70%
	98,51 - 99,5	0,90%	0,60%	0,30%	0,20%	0,10%	0,05%	-0,35%	-0,75%	-0,90%
	97,51 - 98,5	0,60%	0,30%	0,20%	0,10%	0,05%	0,00%	-0,40%	-1,00%	-1,10%
	96,51 - 97,5	0,40%	0,15%	0,10%	0,05%	0,00%	-0,10%	-0,50%	-1,25%	-1,50%
	95,01 - 96,5	0,30%	0,10%	0,05%	0,00%	-0,10%	-0,20%	-0,60%	-1,50%	-1,90%
	90,01 - 95	-0,05%	-0,15%	-0,20%	-0,25%	-0,30%	-0,50%	-0,75%	-1,75%	-2,30%
	70,01 - 90	-0,30%	-0,40%	-0,50%	-0,60%	-0,70%	-0,80%	-1,00%	-2,25%	-2,70%
	0 - 70	-0,50%	-0,70%	-0,90%	-1,10%	-1,50%	-1,90%	-2,30%	-2,70%	-3,00%

Matrix outcome

SoS %	**99,24%**
NoStock%	**1,00%**
Type Matrix Result	**0,20%**
	1 079,01

FARFETCH

STEP 3: CALCULATE ANY ADDITIONAL COSTS SUCH AS:

- Packaging Costs
- No Stock Vouchers

Additional Costs		
Packaging Cost	$	2 884,50
NoStock Vouchers	$	198,00

STEP 4: CALCULATE EXTRA INCENTIVE FOR ORDERS SENT IN < 1 DAY

% Orders with NET SOS < 1 day	Incentive
0% -79%	0% Packaging Cost Refunded
80% -89%	25% Packaging Cost Refunded + 0,2% ATV
90% -100%	100% Packaging Cost Refunded + 0,4% ATV

Incentive/Penalties		
Matrix	$	1 079,01
Extra Incentive SoS	$	1 800,14
No Stock Vouchers	$	-198,00
Wrong Item Rule		Compliant
Total Incentives:	**$**	**2 681,15**

Result: Because this partner was compliant with the Wrong Item Rule, they were able to achieve a total of **$2681.15** in the given month, after the additional costs were deducted.

Appendix B

Operational Targets for 2019 (OKRs) per Tier and Region

NO STOCK TARGET 2019

	2018	TARGET	
Boutique	1,4%	1,3%	-6,3%
T0 - Key	1,1%	1,1%	-1,7%
T1 - Important	1,3%	1,3%	-2,3%
Tx - Standard	1,8%	1,5%	-16,3%
Non EU Boutique	3,3%	3,0%	-9,2%
Brand	3,5%	2,2%	-38,0%
B0 - Key	4,7%	2,9%	-38,3%
B1 - Important	4,5%	2,3%	-49,3%
Bx - Standard	2,3%	1,7%	-27,7%
Grand Total	**1,7%**	**1,4%**	**-13,6%**

	2018	TARGET	
APAC	2,3%	1,9%	-18,0%
BR	2,2%	2,0%	-8,5%
CN	3,4%	2,4%	-27,4%
EU	1,5%	1,3%	-10,1%
JP	3,1%	2,5%	-19,5%
US	4,3%	2,8%	-34,1%
Grand Total	**1,7%**	**1,4%**	**-13,6%**

SPEED OF SENDING TARGET 2019 - 2 days

Less than 2 days

	2018	TARGET	
Boutique	96,2%	96,3%	0,2%
T0 - Key	95,7%	96,0%	0,3%
T1 - Important	97,2%	97,0%	-0,2%
Tx - Standard	98,1%	97,5%	-0,7%
Non EU Boutique	92,5%	94,5%	2,2%
Brand	88,2%	93,0%	5,4%
B0 - Key	87,5%	93,0%	6,3%
B1 - Important	91,8%	93,0%	1,3%
Bx - Standard	86,9%	93,0%	7,0%
Grand Total	**95,3%**	**96,0%**	**0,7%**

	2018	TARGET	
APAC	96,8%	96,7%	-0,2%
BR	69,7%	85,8%	23,0%
CN	74,4%	98,0%	31,7%
EU	96,0%	96,6%	0,6%
JP	90,4%	94,8%	4,9%
US	92,1%	94,6%	2,7%
Grand Total	**95,3%**	**96,0%**	**0,7%**

SPEED OF SENDING TARGET 2019 - 1 day

Less than 1 day

	2018	TARGET	
Boutique	75,4%	80,0%	6,1%
T0 - Key	73,3%	79,8%	8,8%
T1 - Important	79,4%	82,2%	3,5%
Tx - Standard	81,8%	83,2%	1,8%
Non EU Boutique	68,9%	76,6%	11,1%
Brand	59,6%	76,9%	29,0%
B0 - Key	56,5%	74,6%	32,2%
B1 - Important	63,1%	76,7%	21,6%
Bx - Standard	59,9%	78,4%	30,9%
Grand Total	**73,7%**	**80,0%**	**8,5%**

	2018	TARGET	
APAC	79,5%	82,2%	3,5%
BR	40,9%	73,7%	80,1%
CN	49,2%	74,0%	50,4%
EU	74,8%	80,3%	7,3%
JP	62,1%	76,5%	23,1%
US	65,7%	76,8%	16,9%
Grand Total	**73,7%**	**80,0%**	**8,5%**